Aalto University
School of Business

Forecasting for Intermittent Spare Parts in Single-Echelon Multi-Location and Multi-Item Logistics Network Case KONE Global Spares Supply

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Nnamdi Oguji

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Department of Information and Service Economy
Aalto University
School of Business

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Oguji Nnamdi
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Professor Markku Kuula

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ABSTRACT

The objective of this thesis is to test existing forecasting models for intermittence demand SKU's and implement the best forecast model that suits the inventory control policy of the case company. The optimal forecasting model was selected based on the model that produces optimal performance in terms of customer service levels, inventory total cost and inventory value.

Intermittence demand type was categorized based on degree of lumpiness, erratic, smooth-intermittence and intermittent types. The quantitative data set comprised of historical demand information from 2010-2012 (36 months period) for sixteen thousand stock keeping units (SKU) in the three central distribution centers of the case company. Algorithms for the different forecasting models was developed using VBA programming in Excel 2007 and simulated against the demand data. Explorative approach was used to gather information regarding new material introduction process, forecasting parameters used in the software package (Servigistics) and how the results of the research can be implemented in the case organization.

The result of the analysis shows that traditional forecast accuracy measure is inadequate for selecting best forecast model. Nevertheless, our result shows that no forecast method (Simple Exponential Smoothening (SES), Croston and Modified Croston (SBA) explicitly showed superior performance in all the traditional measures utilized. When stock control measure was utilized Croston showed superior customer service levels of 1% to SES and 1.4% to SBA. The superior customer service levels come with a 1% increase in total cost. The findings of the thesis also suggest the need for amending the outlier management settings in the software system and to customized tracking signal in the forecast review board to enable the prioritization of review reasons in degree of descending order of stock value and tracking signal estimates.

Keywords: Forecasting Performance, Intermittence, Croston, Continuous Review System.

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For my Beloved Wife (Cindy Oguji) and Son (Chidera Oguji), I will always love you. All my driving force and motivation stems from your support and love for me.

Hopefully, this would be my last master's thesis while seeking for a brighter professional career in international logistics and supply chain management.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Background

Demand forecasting plays a significant role in inventory planning and production. Accurate forecasting makes it possible to meet customer service levels, manage inventory levels in warehouses and maintain accurate inventory polices necessary to minimize excess stocks and warehouse space. The literature has established several forecasting models for various demand patterns using various method of analysis. Time series and casual methods are usually employed for quantitative methods while Delphi method is mostly utilize for qualitative models (Armstrong, 2006). Time series models such as naive method, moving average, weight moving average, exponential smoothing, Croston, bootstrapping, seasonality analysis, multiplicative decomposition and additive decomposition have been suggested to deal with several demand patterns. Among this demand patterns, intermittence demand pattern is one of the most challenging demand pattern. It has been estimated that intermittence demand items accounts for roughly 60% of total stock value (Johnston et., 2003) and are prevalent in aerospace, automotive, military, IT sectors (Teunter et al., 2011) and spare parts business.

Intermittent demand is a peculiar and challenging demand pattern in spare parts business. It is used to describe demand pattern in which there are several months/periods of no demand in-between months of demand. Intermittence can vary in size of demand in a particular period with some periods showing no demand at all and some other periods showing erratic/lumpy and slow moving demand. This type of demand is difficult to predict, and errors in prediction are usually costly because it creates excess stock and reduces service performance.

An estimated analysis of the case company shows that about thirty thousand stock items (~40% of the total stocks items) within the case company has intermittence demand. Intermittence is defined as when mean inter-demand intervals is greater than 1.25 forecast revision period or when the number of zeros demand within 13months demand is greater than or equal to 3 (Syntetos et al. 2005b; Boylan et al. 2008). This translates into 17% of the entire stock value of the case company in its three central distribution centers amounting to 3.92million Euros. More so, new spare parts introduced as stock items for the case company contributes to about 36% of the intermittence demand items. 28% of intermittence demand items ends up as dead stock while 18% end ups as excess stock.

The case company defines excess stock as when more than twenty-four months historical consumption is on-hand in stock and dead stock as when there are no sales for a spare part for two or more years. Excess and dead stocks have been researched thoroughly in extant literature (See Brown et al. 1964; Cobbart & Oudheusden 1996; Song & Zipkin 1996; Song & Lau 2004; van Jaarsveld & Dekker 2011; Prince & Dekker, 2011). Conclusions from these studies suggest that forecast inaccuracy and overzealous purchase practices contributes to the piled up of excess inventory.

The purpose of this thesis is to: (1) test several intermittence demand forecasting models suggested by empirical literature and recommend which forecasting model performs better for the case company in terms of meeting customer service levels, reduces inventory total cost, inventory value and piled up of excess stocks in inventory. (2) To explore how the outcomes of (1) can be implemented in the case company.

1.2. Research Questions and Limitations

Different spare parts are said to be associated with different demand patterns which in turn requires different forecasting model (Heinecke et al., 2011). One of such demand pattern that has drawn considerable research attention is intermittence demand patterns due to their complex nature.

Literature on intermittence forecasting models have so far utilized Croston (Croston 1972), modified Croston (See Syntetos, 2001; Leven & Segerstedt, 2004; Syntetos & Boylan 2005) bootstrapping (Willemain et al., 2004) and simple exponential smoothing (Eaves & Kingsman , 2004; Syntetos & Boylan, 2005; Wallström & Segerstedt 2010) models to forecast intermittence demand. These studies have suggested several improvements for intermittence demand forecasting. However, further attention is needed because studies so far have somewhat treated traditionally forecasting and stock control as mutually independent inventory parameters (Strijbosch et al., 2011; Syntetos et al., 2009).

Four streams of studies have made attempt to address this issue, but more attention is needed to compare the relationship between forecasting and inventory control systems. The first stream of studies tends to link forecasting to obsolescence. Considering that intermittence items significantly ends up as obsolescence stock than fast moving items, studies have linked intermittence forecasting models that control for obsolescence rate by providing no forecast values after several periods of no demand (Teunter et al., 2011).

The second stream of studies tends to link forecasting to inventory classifications. These studies have linked classification of inventory models to include degree of intermittence and erratic nature of demand in order to aid selection of appropriate forecasting models for which ABC analysis is not well suited for (e.g., Syntetos, et al., 2005; 2011 Heinecke et al., 2011). Syntetos et al. (2005) examined the performance of intermittence forecasting models such as Croston, simple exponential smoothing and Syntetos & Boylan approximation (SBA-Syntetos & Boylan 2005). They found out that SBA performs better where intermittence is greater than 1.32 and squared coefficient of variation (CV^2) is greater than 0.49. They classified SKU according to degree of intermittence and degree of erraticness. Consequently, SKU with less than 1.25 mean inter-arrival times is classified as fast moving items.

The third stream of studies tends to link forecasting models to the timing of forecasts and ordering policies. Syntetos & Boylan (2005) explored the accuracy of intermittence demand estimates considering timing of forecast (i.e., all points in time and time periods immediately after a demand occurrence). Their findings suggest that SES performs better than SBA for time periods immediately after demand occurs. However, for all time periods their finding was inconclusive. Leven & Segerstedt, (2004) studied the implementation of their modified Croston forecasting model in periodic review systems and concluded that modified Croston performs better for intermittence demand items than Croston. They suggested the application of this approach to continuous review systems but studies linking intermittence forecasting models in a continuous inventory control systems are limited. For this reason, Leven & Segerstedt, (2004) concluded that some theoretical coherent approaches that address this interaction are still very much needed. Boylan et al. (2008) using case study extended the outcomes of forecasting for intermittent demand items to stock control in a continuous re-order point, order quantity (s, Q) review system by showing that the application of Syntetos & Boylan approximation (SBA) (Syntetos & Boylan 2005, 2006) led to significant reduction in total inventory value while compromising customer service levels. Syntetos et al. (2009) extended the interaction between forecasting and stock control to account for lead time. As with the case with intermittent demand items were lead time is often less than average inter-arrival time, Syntetos and colleagues proposed new periodic review systems that accounts for both inter-arrival time and demand sizes in periodic review systems.

The fourth stream of studies tends to argue for the need to link forecasting to multi-echelon optimization. For example, Kalchschmidt et al. (2003) recommended separating demand patterns in their respective patterns and derive their respective ordering policies accordingly to enhance the operative performance of inventory management. Empirical studies exploring this linkage are somewhat scanty. Heikkilä, (2011) studied the optimization of service part inventory and lateral transshipment of the case company under study. The study aimed at deriving safety stocks and re-order point levels for every chosen pair in the three distribution centers that reduces total inventory cost and improves customer service levels. He recommended that the lack of implementation of accurate forecast models for intermittence demand spares is hindering the total value that could be derived from the Single-Echelon Optimization (SEO).

Thus far, studies have linked forecasting to obsolescence, forecasting based SKU classification and timing of forecast. Empirical studies linking forecasting to lateral transshipment need further empirical studies. Literature on intermittence forecast has not compared the performance of naive model with other intermittence forecast estimates. Extending intermittence forecast estimates to include naive model would be an interesting area from both theoretical concern and practitioner perspective (Heinecke et al., 2011). It has been argued that the best demands forecasting methods for minimizing inventory costs varies with the inventory policy used and lead time (Liao & Chang, 2010). However, preliminary results of comparing forecast outcomes to other inventory control system indicated no significant differences (Boylan et al., 2008). Consequently, further studies are needed to throw more light on the relationship between forecasting and stock control.

Based on this summary, the purpose of this research is to test existing forecasting models for intermittence demand pattern and choose the intermittent demand estimates that will significantly increases forecasting performance for the case company in terms of increasing customer service levels and reducing total inventory cost. Consequently, the thesis aim to answer the following research questions:

1. Which of these forecasting models: crotons models, simple exponential smoothing model, naive model (same as last year forecast) perform better for intermittence demand items for KONE global spares supply unit?
2. Which inventory control policy (s, Q) vs. (s, S) in continuous review systems maximizes the advantages of the best forecasting models for intermittence items?
3. Does improvement in intermittence demand forecasting improve multi-echelon optimization?
4. Explore how the results of the thesis can be implemented in the case organization

By (s, Q) inventory control policy, I refer to inventory control systems where a firm place orders of size Q, whenever its inventory position reaches a re-order point (s) (Harris, 1913). (S, s) control policy are inventory control policy when the on-hand inventory drops to a prefixed level s ($0 < s < S - s$), an order for Q (= S - s) units is placed (Kalpakam & Sapna, 1994).

This study has several limitations. First, the study did not utilize lateral transshipment policy from the literature when exploring it's linkage to forecasting outcomes. This is because the case company requires that the linkage should be based on the software they are using for inventory planning and optimization. For copyright reasons, the formula for lateral transshipment policy and multi-echelon optimization performance was not disclosed in the study. More so, the relationship between forecasting outcomes and lateral transshipment policy was not reported because by the time the thesis was completed, more time is required in the future to monitor forecasting outcomes and multi-echelon performance observed in the planning software. The study does not address overall the excess and dead stock challenges facing the case company. Future studies should attempt to link forecasting and dead stock reduction using simplistic models that can applied in real life case. Finally, the literature has established several methods for the derivation of optimal order quantity (S). However, a simple model based on the annual average consumption was utilized. Future studies should attempt to utilize other ways for derivation of practical optimal order-up-to levels which would throw more light on the relationships between forecasting and stock control policy.

1.3. Research Strategy

According to Yin (2009), a research design is a logical sequence that connects the empirical data to a study initial research equations and ultimately to its conclusions. According to him, a research design should have research questions, unit of analysis, propositions and logic to link the data to the proposition and criteria for interpreting the findings

Research question is one of the first facets of a research design. Philosophically, it has been argued that the research question for a study should be thought about in relation to epistemological assumptions. I concur to the pragmatic perspective entailing that as a researcher, I’m more concerned about what data and analyses are needed to meet the goals of the research and answer the questions at hand. Thus, I’ll choose the methods that are most likely to provide evidence useful for answering the research questions given the inquiry objectives, research context, and the available resources (Jang, et al., 2008).

There are ten major types of research strategy and data collection method in purchasing and supply chain management identified in extant literature (See Wynstra, 2010). In order to fulfill the objective of this thesis, a single case study research method will be utilized. To provide answers to the research questions, both inductive and deductive (mixed method) approaches will be used.

Quantitative data analysis derived from primary data source is utilized for testing the application of the forecasting models. The explorative/inductive part requires qualitative approach to data collection. Face-to-face qualitative interviews with the various stakeholders in the global technical team, inventory planning and purchasing team will be done to explore the new spare parts introduction process and how the outcomes of the thesis can be implemented in the chosen organization.

This thesis is focused on the company level and seeks to test which forecasting model is best suited for the intermittence demand items of the case organization. Thus, the unit of analysis is a single case study. The case company is KONE Global Spares Supply unit. As emphasized by Yin, (2009), every research design should have a unit of analysis and the research question should reflect the unit of analysis and the unit of analysis should be at the level being addressed by the main research questions.

Finally, the chapters in this thesis will address several inventory and logistics issues that will enable me provide answers to the research questions. At the end of each chapter and section, a summary of the contributions of literature and analysis will be made. Based on this summary, a theoretical framework is developed in section 2.5 linking the research questions to the literature review. The theoretical framework will be tested in the empirical section (Chapter 3).

1.4. Outline of the study

This thesis will comprise of four chapters. Chapter one discussed background and general introduction regarding the aim of the study that includes the research questions and outline of the study. Chapter two will focus on literature review necessary to provide answers to the chosen research questions. The literature review analyzes relevant issues in forecasting, inventory, logistics and supply chain management.

Chapter three discusses the methodology. In this chapter, the inventory management and forecasting process of the chosen organization will be discussed. Data collection and method of analysis will also be elaborated. The data collection and data analysis will be described systematically linking it to the theoretical framework.

Chapter four will discuss the results of the various data analysis and the theoretical implications. In this chapter, the results of the analysis will be described and linked to the theoretical framework and chosen research questions. Chapter five discusses the conclusions of the research. The research summary, contribution to theory, comments from the company regarding the thesis and a little insight on how these results are implemented in the chosen organization will be discussed. Finally, recommendations for future studies are stated.

2. LITERATURE REVIEW

2.1 Spare Parts Inventory Classification

A review of existing research on inventory classifications for spare parts is shown in Table 1. From the table, there are three streams of studies on inventory classification for spare parts business. The first stream refers to traditional inventory classification which discusses the traditional ABC/XYZ classification and its usage in inventory planning and management. The second stream is a composite of the traditional classification and other variables which contributing authors aim to show how these combinations aid inventory planning better than the traditional classification. The third stream of inventory classification has sufficed however only one study has applied it in spare parts business. This third stream of study is the forecasting based classification which contributing authors argue that the existing classification is not well suited for selection of appropriate forecasting methods. Section 2.1.1 to 2.1.3 discusses the various streams of SKU classification in details.

2.1.1 Traditional Inventory Classification

ABC classification is the most widely used inventory classification mainly used in practice to determine service requirements. It is built based on Pareto, (1906) and is used to rank Stock keeping Units (SKU's) in decreasing order of demand volume or demand value. Thus, SKU's with highest demand volume multiplied by price are ranked as A, while those with lowest demand volume multiplied by price is ranked as C. The ranks are in decreasing order of A, B, and C which represents about 20%, 30%, 50% respectively. Some organizations also used a fourth class named D. The aim of this classification is to enable organization to focus on a relatively small number of products (A items) that represents a major part of the sales volume of which relative reductions in inventory cost can be achieved (Tim, et al., 2012).

Table 1: Different Streams of SKU Classification

Authors	Classification criteria	SKU classification type	Industry
Cavalieri et al. (2008)	• Criticality • Unit cost • Demand Volume • Number of installations	Composite criteria	Spare parts (Process industry)
Duchessi et al., (1988)	• Inventory cost • Criticality • Unit cost • Demand Volume	Composite criteria	Spare parts
Ernst & Cohen (1990)	• Criticality • Unit cost • Demand Volume • Lead time • Product life cycle	Composite criteria	spare parts (Automotive)
Huiskonen (2001)	• Criticality • Demand volume • Unit cost¨ • Specificity • Demand Pattern • Predictability	Composite criteria	Spare parts
Kobbacy & Liang (1999)	• Demand volume • Lead time • Demand Pattern	Composite criteria	Spare parts (Manufacturing & Airline)

Authors	Classification criteria	SKU classification type	Industry
Mukhopadhyay et al. (2003)	• Demand volume • Unit cost • Criticality	Composite criteria	Spare parts (Mining)
Paakki et al. (2011)	• Demand value • Demand variability • Supplier risks	Composite criteria	Spare parts
Partovi & Anandarajan (2002)	• Demand volume • Unit cost • Ordering cost • Lead time	Composite criteria	Spare parts (Pharmaceutical)
Partovi & Hopton (1994)	• Demand volume • Unit cost • Criticality • Lead time	Composite criteria	Spare parts (Pharmaceutical)
Porras & Dekker (2008)	• Demand volume • Unit cost • Criticality	Composite criteria	Spare parts (Oil refinery)
Syntetos et al. (2009)	• Demand Value	Traditional criteria	Spare parts
Teunter et al.(2010)	• Demand volume • Demand value • Criticality(backorder cost)	Composite	Spare parts (textile machinery & automotive)
Boylan et al. (2008)	• Demand-intervals • Demand size & variance	Forecasting Criteria	Motor spare parts

Some organizations use the demand-volume ABC classification; some others use demand-value criteria (for a review, see Tim et al. 2012). In their study on demand categorization in a European spare parts logistics network, Syntetos et al. (2009) finds out that the replacement of demand-volume ABC based classification by demand-value classification lead to significant organizational benefits. In contrarily, Pflitsch, (2008) found out that demand-volume criteria is more effective in reducing inventory cost and maximizing service levels. Context specific reason may be the reason for this contradictory finding. For example, the study by Syntetos and colleagues focuses on spare parts business and their assumption is that higher price should entail higher holding cost, which results in cost savings for demand-value criteria.

The importance of this classification in inventory management is that organizations use these classifications to determine service levels. Thus, (A) class items are considered the most critical for organizations in terms of value, thus should require the highest service levels to avoid frequent back orders. This argument suggest that back orders for (A) items is costly than back orders for C items. Knod & Schonberger, (2001), and others (Viswanathan & Bhatnagar, 2005; Teunter et al. 2010) argued that C SKU's should get the highest service levels because the cost of managing the back orders caused by these items (e.g., emergency shipments) is far much larger than the cost of holding these group of items in stock. Similarly, Syntetos et al. (2011) argued that if class A items receive the most service levels using the demand-value ABC criterion, then SKU's with the higher price which ultimately have the highest storage cost will have relatively larger stock levels resulting in cost inefficiencies.

2.1.2 Composite Inventory classification

Composite inventory classification tends to combine the traditional inventory classification in addition to other inventory variables and other context specific variants for inventory management purposes.

One of the well-known traditional-composite criteria is the XYZ inventory classification method which is based on demand variability. Some authors or organization use the XYZ classification as demand volume criteria. Originally, the XYZ classification is done by calculating the variation coefficient (VC) of SKU's (VC=standard deviation of demand in period N/Average consumption in period N * 100) and then sorting them in increasing order of demand variation XYZ representing 20%, 30% and 50% respectively. That is:

$$\mathrm{VC} = \frac{\sigma}{\mu} * 100$$

Thus, X items have low variation in demand, while Z items have highest variation in demand. This classification allows for management to implement different control strategies for the different groups. For example, X items should be checked more regularly because they have lowest variation in demand. In practical sense, it is most often combined with ABC analysis to make supply planning and review policy decisions. For example continuous review systems are far suitable for AX, BX, and CX items, while periodic review systems are suitable for AZ, BZ and CZ items.

From Table 1, in addition to traditional inventory (demand value/demand volume) criteria, composite classification utilizes other variables such as criticality, lead time, demand pattern and product life cycle for spare parts SKU classification. The reason for this composite criteria is because the traditional demand-volume/demand-value criterion was not developed from an inventory cost perspective, hence does not maximize cost-service efficiency (Teunter et al., 2010).

Teunter et al. (2010) derived a composite cost-criterion based inventory classification in addition to traditional ABC classification that maintains adequate service levels while reducing inventory costs. Their model is represented by ranking the SKU's based on descending order of the value of $[\frac{bD}{\mathrm{hQ}}]$.

Where b represents the criticality measured as the shortage cost/backorder cost. D is the demand volume, h is the unit holding cost, and Q is the average order size. From this value the cycle service level per class is then calculated and SKU's with the higher optimal cycle service level $[\frac{bD}{\mathrm{hQ}}]$ gets the higher rank. Teunter et al. (2010) showed that this model outperformed the single demand-value/demand-volume criteria and Zang et al. (2001) composite model $[\frac{Di}{\mathrm{h}^2\mathrm{Li}}]$ on cycle service level (1-probability of stock-out).

Both Teunter et al. (2010) cost criteria and ABC demand-volume criteria ranks SKU's higher if the demand volume is larger. However, the difference between them is that while on one hand, the cost criterion ranks an SKU higher if the holding cost is lower. On the other hand, the demand value criterion assumes that a higher price implies a higher holding cost thus ranks an SKU higher if the holding cost is higher.

Paakki et al. (2011) developed spare parts multi-criteria categorization for spare parts distribution chain performance based on demand and supply categorization. The demand categorization took cognizance of spare parts value and demand variability while supply categorization is based on availability risks. Seven categories were developed based on the combination of supply risks and demand variability. This model makes it feasible for the implementation of inventory and control policies for managing high value items that constitute greater shortage cost for the case organization.

Other surrogates of composite criterion or multi-attribute criterion on inventory classification have sufficed though not applied in spare parts business (e.g., Ramanathan 2006; Ng 2007; Zhou and Fan 2007; Chen et al. 2008). Ng (2007) used weighted linear optimization model on three criteria such as annual dollar usage, average unit cost and lead time for inventory classification. The values obtained from these criteria are transformed into scalar scores which are further ranked in terms of ABC classification. Similarly, Zuo and Fan (2007) used the average unit cost, annual dollar usage, and lead time to derive a set of criterion weights for each items and assign a normalized score to this item for further ABC analysis. Ramanathan, (2006) and Chen et al. (2008) included critical factor criteria in addition to the three criterions used in Ng, (2007) and Zhou and Fan (2007).

2.1.3 Forecasting Based Classification

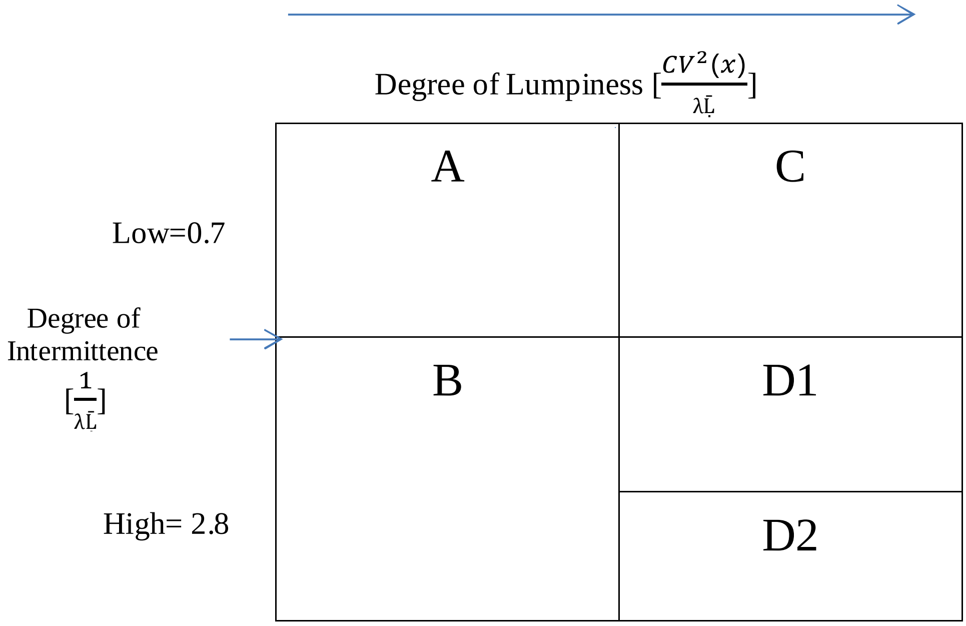
The previous section has shown the importance of inventory classification for stock-holdings and customer service levels. The above studies show significant improvement in inventory categorization from the traditional single-criteria to the composite/multi-criteria categorization. Recent studies have indicated that, though there is significant progress in the inventory categorization literature, however, demand categorization that enables the application of adequate forecasting models is still at their infant stage.

One of the reasons for demand categorization for forecasting model is because the traditional ABC classification and composite models are not well suited for selection of appropriate forecasting models because it does not take into cognizance the importance of demand and customer characteristics (Syntetos et al., 2011). In other words, both the traditional and the composite criterion had demand-value criteria, however, does not consider the demand rate, intermittence and lumpiness of the demand which are crucial factors in identifying appropriate forecasting models. From table, 1, it is obvious that the application of forecasting based categorization have not sufficed for spare parts business (excluding Boylan et al. 2008 who applied Syntetos et al. (2005) typology for forecasting based SKU classification on data sets that includes motor spare parts)

Williams (1984) is one of such first studies that categorized inventory based on demand type to enable the application of adequate forecasting models. Their classification split the variance of demand during lead time into three different forms namely: sporadic, slow moving and smooth. These classifications were based on how large or small the number of lead times between successive demands [$\frac{1}{\lambda \bar{L}}$] and the lumpiness of demand model [$\frac{CV^2(x)}{\lambda \bar{L}}$]. $CV^2_{(x)}$ represents the squared coefficient of variation of the distribution of demand size, λ represents the mean demand arrival rate and $\bar{L}$ represents the lead time mean.

Figure 1 below shows Williams forecasting based demand classification. D1 items are sporadic items for which demand is very lumpy or [$\frac{CV^2(x)}{\lambda \bar{L}}$] > 0.5. D2 items are highly sporadic items that are extremely lumpy. B items are slow moving items that are not often demanded with high intermittence [$\frac{CV^2(x)}{\lambda \bar{L}}$] <=0.5. Finally A and C items are smooth items with low intermittence but varying degree of lumpiness. From this categorization forecasting based models that are appropriate can be applied. For instance, Croston forecasting model have been shown to empirically perform better for (A) items.

Figure 1: Forecasting Based Demand Classification (Williams, 1984)



Eaves (2002) suggest a modification to William's framework on the notion that Williams's framework did not adequately describe the demand structure rather it does consider the effect of lead time variability. Eaves classification has demand size variability, transaction rate variability and lead time variability as shown in Figure 2. Accordingly, A items are classified as smooth items, B items are classified as slow moving items, D1 items are classified as erratic items and D2 items are classified as highly erratic items.

Syntetos et al. (2005b) extended Eaves classification by classifying demand based on the degree of intermittence and the degree of erratic nature of the demand. Figure 3 shows the classification of inventory based on demand patterns and their respective forecasting models empirically proven to perform better (using mean squared error). The erraticness is evaluated as the square of the standard deviation of the nonzero demand value divide by the square of the average non-zero demand items. The greater the erraticness, the demand category becomes either of less intermittent or more intermittent. The lower the erraticness, the demand category becomes either of a smooth/less intermittent type or of high intermittence.

Figure 2: Forecasting Based Demand Classification (Eaves, 2002)

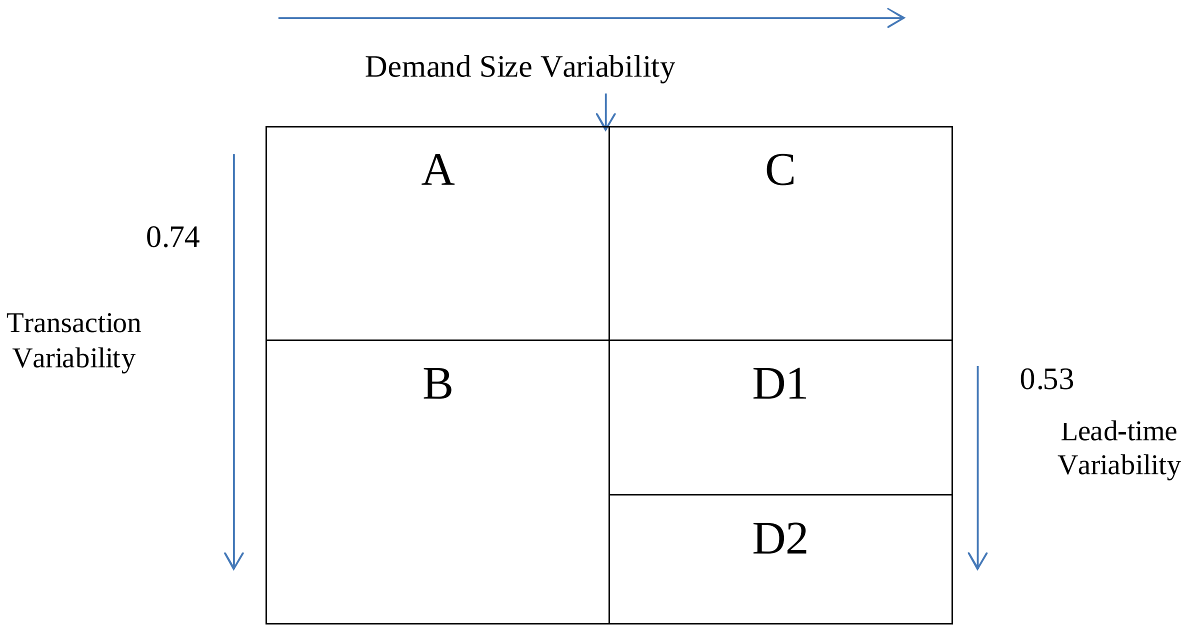
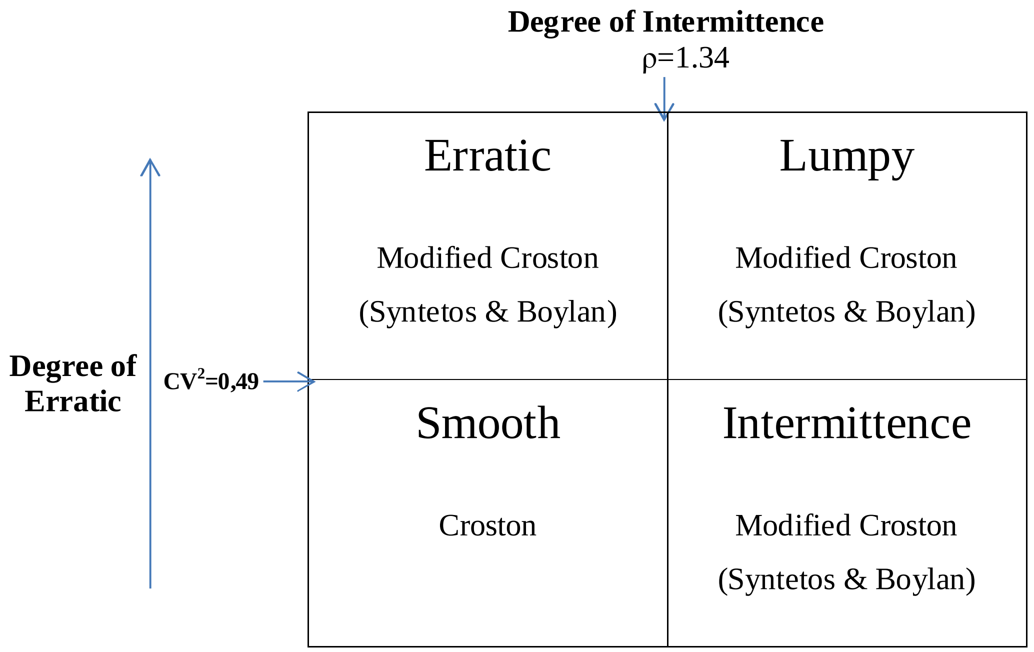


Figure 3: Forecasting Based Demand Classification (Syntetos et al., 2005)



Syntetos and colleagues framework for classifying inventory for forecasting purposes based on demand patterns is an interesting contribution in the extant literature. The interaction of the degree of intermittence and erraticness to traditional inventory classification (e.g., demand-value criterion) would be an interesting area for management. Management is far much interested in the value of items that contributes significantly to their bottom line. Thus, interacting this with demand-value and recommending intermittence forecasting model that optimizes cost-service level efficiency would be an area of managerial interest.

In summary, the foregoing discussions suggest that the aim of SKU classification is for inventory management purposes. However, the focus may vary. As the literature pointed out, recent studies are seeking for classifications aimed at forecasting purposes. Other studies used composite measures and some studies used the traditional SKU classification. No context could be identified under which a certain criteria can be used. Unlike the forecasting based model, demand value is one important criterion for both the traditional and composite classification. This may be because of managerial concern to focus resources on more value-driven criteria. While the contribution of forecasting based classification is of significance importance, to increase its attractiveness to practitioners, effort should be made to include spare parts value and or criticality.

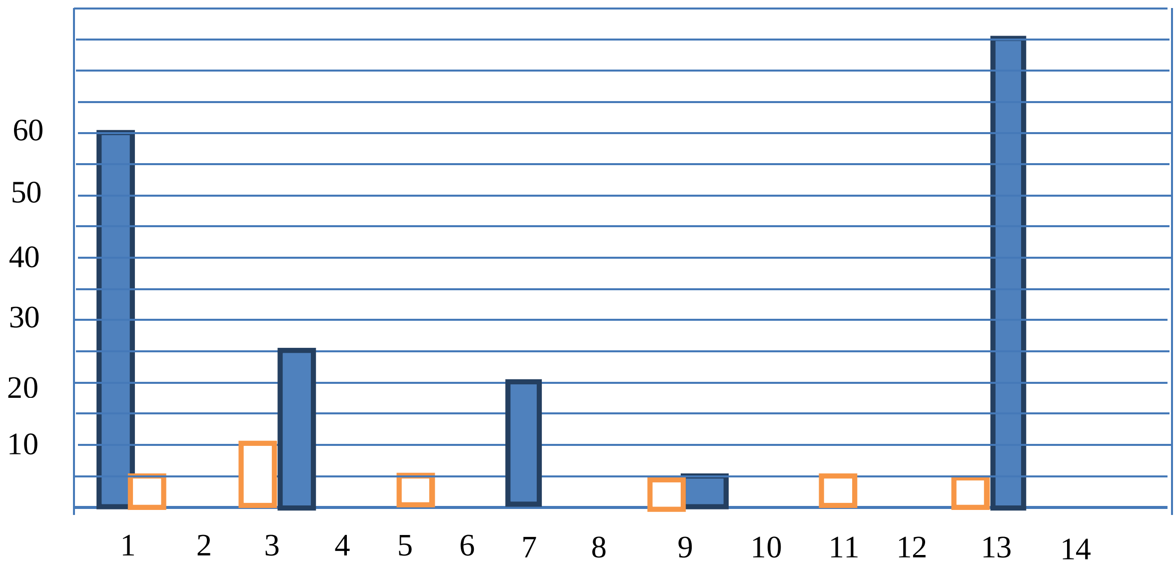
2.2 Forecasting Models for Intermittence Demand

This section discusses the meaning of intermittence demand and the various criteria used in extant literature for the classification of intermittence. More so, this section discusses the different forecasting models for intermittence demand items.

2.2.1 What is Intermittence Demand?

Intermittence demand are a form of demand in which there is variation in the frequency of orders and variation in the size of customer orders with some time periods showing no demand at all and when demand occurs, the demand size/size of customer order may be variable. Intermittent demand may occur as a step process to obsoleteness for fast moving items. Thus, an item that moves regularly gradually becomes dead. Intermittence demand items are said to be at the greatest risks of obsoleteness and constitute a greater percentage of total stock value in spare parts business. An example of intermittence demand is shown in figure 4 below.

Figure 4: Example of Intermittence Demand Pattern



The figure above shows a 14 months demand period. The blue and white boxes show two different items with some periods of demand and some periods of no demand. The blue one has 9-months of zero demand while the white one has 8-months of zero demand. X represents periods of demand and 0 represents periods of no demand.

Croston (1972) defines Intermittence as when the mean inter-demand interval is greater than 1.25. To check for intermittence for these two items, we represent their demand as follows:

A(Blue) = X,0,X,0,0,0,X,0,X,0,0,0,X,0 = (1+2+4+2+4+1)/6=14/6=2.3

B(White)= X,0,X,0,X,0,0,0,X,0,X,0,X, 0 = (1+2+2+4+2+2+1)/7=14/7=2.0

For Yuan & Cai, (2008) the intermittence would be expressed as:

A(Blue) = X,0,X,0,0,0,X,,0,X,0,0,0,X, = (1+2+4+2+4)/5=13/5=2.6

B(White)= X,0,X,0,X,0,0,0,X,0,X,0,X, = (1+2+2+4+2+2)/6=13/6=2.17

The difference between Yuan & Cai, (2008) and Croston is that Yuan & Cai, method assumes that if the demand starts with leading zero demand and ends with zero value, these leading and ending zeros should be eliminated from the sample because they may provide inaccurate information about the first inter-arrival interval because they can be part of a longer period of zero demands.

While Croston defines intermittence as when the mean inter-demand interval is greater than 1.25, Boyan et al. (2008) defines intermittence demand as SKU's with three or more zero-demand periods in the latest 13-periods. They classified the number of zeros and their corresponding mean inter-demand interval as shown in Table 2.

Table 2: Number of zero-demand periods and corresponding intermittence level (Boylan et al., 2008)

No. of zero's	Intermittence (ρ)
5-to-7	1.63-2.17
6-to-8	1.86-2.6
2-to-3	1.18-130
2-to-4	1.18-1.44

The problem with this classification is that it does not define the limit for intermittence. For example if the number of zero is 12 out of 13 periods why should it be classified as intermittence items? Such type of demand pattern has no inter-arrival time. Such items can for example be subjected to (S-1, S) policy in which whenever there is any demand, the replenishment quantity is the quantity currently demanded i.e. replenishment quantity S (= S-1) quantity currently demanded.

As with Syntetos et al. (2011), Boylan et al. (2008) and Syntetos et al. (2005b) define intermittence based on the degree of degree of erraticness and intermittence to arrive at four types of demand archetypes: Erratic, lumpy, smooth and intermittence demand (See figure 3). The erracticness is computed by taking variance of the non-zero demand items and divide by square of the average of the non-zero demand items. Thus, for figure 1, the blue items will have erraticness of 0.62 and the white items will have erraticness of 0.3. This means that the white items are high intermittent items with low erraticness whereas the blue items are considered lumpy demand items.

2.2.2 Simple Exponential Smoothing

Simple exponential smoothing technique is a forecast technique widely spread in practice. Previously, it was used for forecasting irregulars and intermittence demand items. Its use for intermittence demand items was proven wrong by Croston (1972). Johnston and Boylan (1996) suggest that it is a good estimator for fast moving demand items. Despite its critique for forecasting intermittence items, it is widely used in practice especially where Croston is not in use.

There are other kinds of exponential smoothing methods. Double exponential smoothing and winter's multiplicative forecast method. While, double exponential smoothing is more appropriate where seasonality is not a significant factor, single exponential smoothing is more appropriate where trend and seasonality aren't significant factors. Winter's multiplicative forecast method provides for level, trend and seasonality, each with a weighting factor.

$$F_t = F_{t-1} + \alpha \, (X_{t-1} - F_{t-1}) \qquad (1)$$

F_t = *Forecast estimate for next period (t)*

F_{t-1} = *Exponential smoothing estimate of mean demand for period t,*

X_{t-1} = *Real demand for an item at time* $_{t-1}$,.

α = *Smoothing parameter for mean demand*

In simplistic form, the forecast of a period say F_t is given by multiplying the smoothing parameter with demand of preceding period plus 1 minus the smoothing parameter multiplied by exponential smoothing estimate forecast for preceding period t-1.

2.2.3 Croston Method

Croston (1972) proved that exponential smoothing techniques are inappropriate for use with items with intermittence demand patterns. Their model calculates forecast by taking cognizance of both demand size and interval between demand incidences.

Croston model is similar to simple exponential smoothing method. However, the difference is that, while Croston forecast is renewed only when there is demand, SES renew forecast or updates forecast weather or not demand occurs during a period.

From exponential smoothing (1):

$F_t = F_{t-1} + \alpha\,(X_{t-1} - F_{t-1}),$

$F_{t=}\ \alpha X_{t-1} + F_{t-1}\,(1-\alpha)$

Under this assumption, if we update our demand estimates only when demand occurs, then the expected demand estimate per time period (populated expected value) would not be $\left(\frac{\mu}{\rho}\right)$.

Rather, it would be $E(F_t) = \frac{\mu\,\rho\alpha}{\rho\,[1-(1-\alpha)^{\rho}]} = \left(\frac{\mu\alpha}{1-\beta^{\rho}}\right)$ where $\beta = 1-\alpha$

However, Croston assumes a stochastic model of demand arrival and normally distributed size of demand Y_t $N(\mu,\sigma^2)$, and demand is random with a Bernoulli probability $\left(\frac{1}{\rho}\right)$ occurring every review period. As a result, the inter-demand intervals ρ_t, could be described as that of a geometric distribution with a mean ρ.

The expected value of a geometrically distributed random demand variable F_t is $\left(\frac{1}{\rho}\right)$ and the variance is $\left(\frac{1-p}{p2}\right)$:

Under the condition that a demand size μ occur in a review period, then the expected demand per unit time period is given by:

$E(F_t) = \left(\frac{\mu}{\rho}\right)$ (2)

Croston adds that separate exponential smoothing estimates of the average size of the demand (Y_t) and the average interval between demand incidences (ρ_t) are made after demand occurs. Consequently, if no demand X(t) occurs, the estimates remain the same i.e.

If X(t)=0 then

$Y'_t = Y_{t-1} = Y_t$ and $\rho'_t = \rho_{t-1} = \rho_t$ (3)

Then, the expected estimate of demand per time period would be:

$$E(F'_t) = E\left(\frac{Y_{t-1}}{\rho_{t-1}}\right) = \frac{E(Y_{t-1})}{E(\rho_{t-1})} = \frac{\mu}{\rho}$$

This is similar to naive forecast. But if demand occurs, i.e.

If X(t) >0; then

$Y_{t=} \alpha X_{t-1} + Y_{t-1}(1- \alpha)$ (4) same as (1)

$\rho_{t=} \alpha{*}Q + \rho_{t-1}(1-\alpha)$ (5)

Where Q is actual demand interval in the preceding month; ρ_{t-1} is the smoothened forecast interval in the preceding month. Then:

$$F_t = \left(\frac{Yt}{\rho_t}\right) \quad (6)$$

If demand occurs regularly, Croston is similar to simple exponential smoothing method. More so, Schultz (1987) suggested the use of different estimates for the smoothing constant for inter-demand arrival time and size of demand and applied their estimates to determine base-stock levels (order-up-to) under periodic review inventory-control policy. As a result, equation (5) can be represented as:

$\rho_{t=} \beta{*}Q + \rho_{t-1}(1-\beta)$ (7)

Where β represents the smoothing constant for the inter-arrival time. This system is also used in some software applications such as Sevigistics

2.2.4 Modified Croston Method-SB Approximations

The original Croston method has faced criticisms from researchers that it cannot be used to forecast erratic or lumpy demand data accurately. It has also been criticized of been too positively bias (i.e., the estimation of average demand is greater than what the actual average demand should be given the assumption that demand size is independent of inter-arrival time) and not updating after periods of several months of zero demand.

On one hand there are empirical studies suggesting that Croston perform better for slow moving items (See, Willemain et al., 1994). Some other empirical evidence has suggested that Croston method does not perform better in real world data (See for example Sami & Kingsman, 1997) and have suggested modified versions of Croston method. Sami & Kingsman, (1997) was one of the first to suggest modified versions of Croston. They tested the best forecasting model for slow moving items in a periodic review systems using simulation. Their forecast performance was evaluated based on service levels and total inventory cost using their modified Croston method. Their result shows that 52 week moving average method followed by Croston performs better when accessed based on both service level and cost. Consequently, it was argued that Croston method performs better under well stated assumptions and when its performance is accessed on theoretical generated data. However when real data are used, Syntetos and colleague argued that simple forecasting method may provide more accurate results.

One of the reasons for the low performance of Croston is that it is positively biased. Syntetos & Boylan (2001) analyzed the original Croston estimate and found out that the average estimated demand per time period using Croston method is 64.75% bias when α value is 1. They found out an error in Croston mathematically derivation of the expected estimate of demand per time period. Syntetos & Boylan (2001) argued that if order sizes and inter-arrival times are independent such that

$$\mathrm{E}\left(\frac{Y'_{t-1}}{\rho'_{t-1}}\right) = \mathrm{E}(Y'_{t-1})\ \mathrm{E}\left(\frac{1}{\rho'_{t-1}}\right)$$

And, $\mathrm{E}\left(\frac{1}{\rho'_{t-1}}\right) \neq \frac{1}{E(\rho'_{t-1})}$

Then, Syntetos & Boylan (2001) showed that the expected demand per time period when (α =1) is $\mu\left[-\frac{1}{\rho-1}\log\left(\frac{1}{\rho}\right)\right]$ and not $\left(\frac{\mu}{\rho}\right)$. For example, if the average size of demand (μ) when it occurs is 6, and the average inter-demand interval (ρ) is 3, the average estimated demand per time period using Croston method when α value is 1 will be $\left(\frac{\mu}{\rho}\right)$ i.e (6/3) = 2, whereas it should be

$\mu\left[-\frac{1}{\rho-1}\log\left(\frac{1}{\rho}\right)\right]$ i.e 6*0,231 =1.431. In essence there is about 39.8% bias (percentage error) implicitly incorporated in Croston estimate [N/B: Syntetos & Boylan (2005) found 64.75% bias in Croston, how this was derived is subject to future experimentation]. Syntetos & Boylan (2005) suggest that this bias can be approximated as:

$$(\alpha/2-\alpha)^* Y_t *(\rho_t -1)/\rho_t^{2} \qquad (8)$$

Based on the associated bias in Croston method, Syntetos & Boylan (2001) suggested that Croston method is recommended only for low values of α because the bias becomes pronounced for α values above 0,15. Eaves (2002) suggested that for α values less than or equal to 0.3 the accuracy is within 10 percent.

Generally, it has been agued that one way to to deal with bias (the average error or percentage error) is by subtracting the historical bias from the forecast. Based on this Syntetos & Boylan (2001, 2005) proposed three modification to Croston in attempt to account for the historical bias. The three methods are: (i) Revised Croston's method. (ii) Bias reduction method and (iii) Approximation method.

The revised Croston method: Syntetos & Boylan (2001) proposed that the average demand estimate should be:

$F_t = Y_t/\rho_t, c^{\rho t -1}$

Where c >100 i.e., for any finite value of *c* the method is expected to have a very small bias than the original Croston where $F_t = Y_t/\rho_t$. Thus, the method updates the demand size and $1/\rho_t, c^{\rho t -1}$ instead of the actual interval between transactions after demand occurs with exponential smoothing. This was shown to perform better than Croston on theoretical grounds. They further recommended that this modification should be tested on real demand data in order to quantify the effect of forecasting improvement on inventory control when cost and or service levels are considered.

The bias reduction methods: This method incorporates a deflator to remove the bias in Croston (see equation 7). To estimate new average demand estimate, Syntetos and colleague subtracted the expected bias from Croston's calculation of the mean demand per period.

i.e $F_t = Y_t/\rho_t - [(\alpha/2- \alpha)* Y_t *(\rho_t -1)/ \rho_t^{2}]$ (8)

Syntetos-Boylan Approximation (SBA):

Syntetos & Boylan (2005) went further to test the modified Croston method suggested by them in their study on accuracy of intermittent demand estimates by comparing SBA approximation to original Croston, simple exponential smoothing (SES) and Simple moving average (SMA, 13 periods) on 3000 real intermittent demand data series from the automotive industry. In this study there modified Croston estimate was approximated to be in the form of the original Croston estimate by applying a deflating factor (1- α/2).

$F_t = (1 - \alpha/2)* Y_t/\rho_t$ (9)

Following (Schultz, 1987), It is also possible to use different smoothing constants for the numerator and the denominator. In this case it is the smoothing constant for the denominator (relating to intervals) that should be used in the SBA deflating factor (Syntetos & Boylan, 2005).

The SBA approximation has been shown to perform better under theoretically or traditional performance measures such as MAPE, MSE, MAD, RMSE, RGRMSE, PBt, and ME as well as stock holding value. For example, Eaves & Kingsman (2004) compared the best forecasting model for the ordering and stock-holding of spare parts in UK Royal Air force under a periodic order-up-to R level control policy. They found out that SBA performs better across all demand patterns (smooth, irregular, slow moving and intermittent) using stock holding performance measures. However, using other theoretical generated performance measures, no method showed ambiguous superiority. Similarly, Syntetos, Boylan & Croston (2005) in their study on the categorization of demand patterns found out that SBA performs better than other methods using mean square error. Syntetos, Boylan (2005) in their study on the accuracy of intermittent demand estimates using 3000 real intermittent demand data series from the automotive industry found out that SBA approximation performs better in lumpy, erratic and very erratic intermittent demand pattern using percentage best (the proportion of times that each performance measures such as mean error and relative geometric root mean square error performs best) estimate. Furthermore, Syntetos & Boylan (2006) evaluated the stock control performance of intermittent demand estimates using customer service level and back order cost. When percentage best measure were used to select the forecasting model, SBA method showed superior performance measures than Croston, simple moving average and single exponential smoothing method.

Other modified versions of Croston for intermittent demand has also been proposed (For example, see Leven & Segerstedt 2004; Syntetos 2001). Willemain et al. (2004) developed a non-parametric alternative for forecasting intermittent demands. Their model relies on reconstructing the empirical distribution through a bootstrapping procedure. Although the authors claimed their model tend to perform better than Croston and SES. This method is too complicated to implement in practice and authors have suggested that further empirical evidence is required in order to develop our understanding of the benefits offered by the bootstrapping method (Wang & Syntetos, 2011).

This thesis will focus on Synetetos & Boylan (2001; 2005) i.e., SBA approximation in comparison to Croston method (using different smoothing constants for alpha and beta), simple exponential smoothing and naïve method. The reason is that the other modified Croston methods have been proven to have more bias than the original Croston method. For example, Boylan & Syntetos (2007) and Teunter & Sani (2009) showed that Leven & Segerstedt (2004) modified Croston estimate has more bias than the original Croston method. Teunter & Sani (2009) also showed that, although Syntetos (2001) modified Croston estimate is the least biased method, however it's variance performance is not as good as SBA. There are theoretical arguments that SBA is bias negatively (See, Teunter & Sani, 2009), but its strong variance performance as well as stock control performance on empirical and real life data leaves it exceptionally modest for intermittence demand items than other modified versions.

2.2.5 Naive Forecasting Model

Naïve forecasting is a forecasting model in which the demand for previous month is used as the forecast for next month. It is one of the most simplistic forecasting models. Even the Croston and modified Croston methods behaves like naive forecasting when no demand occurs by returning forecast of previous month as current month forecast. However unlike the naive method, Croston and modified versions updates the forecast when demand occurs.

The use of simple forecasting models in some circumstances has been argued to perform better than complex models. Naive forecasting models have not been empirically tested for intermittence demand items especially in spare parts business. Modest trend % increases have been used in some software providers (e.g., Sevigistics) to update the percentage increase or decrease which can be applied to update historical demand which will be used for forecasting current year.

In summary, four forecasting models simple exponential smoothing (SES), Croston, Syntetos & Boylan (SBA) approximation and Naive method will be used for the empirical section. For the naive method, a scenario of no trend will be used in the empirically section.

2.3 Inventory Control Policy & Supply Planning

One of the main reasons for inventory control is to aid supply planning. Two main methods have dominated the literature. The first stream of literature on inventory control policy is continuous review systems. The second stream of studies refers to periodic review systems. This section discusses this control systems and supply planning models applied to them respectively.

2.3.1 Periodic Review

Periodic review system or (S, T) control system is the second most widely used control system in inventory management (See recent literature review by Williams & Tokar, 2008). The (S, T) model was originally described by Hadley and Whitin (1963). It controls inventory by ordering on pre-set review intervals (T). Thus, upon reaching a review interval (T), an order is placed such that inventory position is brought to some up-to-level (S).

In periodic review systems an optimal review interval is set such that upon this review period (T), a decision regarding how much order is placed to reach a certain inventory level. In essence, there are two basic parameters that are often been controlled for in periodic review systems. The first one is how often to review inventories; and how much to raise the inventories at each review period. Because of the variability in demand, larger safety stocks are often required to avoid shortages, and as a result, holding cost is increased. If safety stocks are decreases, there is a tendency for shortages which may lead to shortage cost and lost sales.

Several supply planning systems has been applied to periodic review systems such as (s, Q), (s, S), (R, S) and (Order Q) models. For example, periodic (s, Q) model is where periodically, if inventory position is less than re-order point (s) order economic order quantity (Q). Periodic (s, S) model is where at every period when each inventory position (x) is analyzed, all items which fall below re-order point ($x<s$) are included in the purchase orders and variable quantity that is between minimum and maximum is ordered. Periodic (R, S) policy is where every period (R) if inventory falls below base stock level, a replenishment is ordered that hits the base stock level (S). Base stock level is given as on hand good (inventory available to meet immediate demand and inventory on order (orders placed but not yet arrived due to lead time) minus the backlog (demand that could not be fulfilled but still has to be delivered). Periodic (order Q) is where periodically, a fixed order quantity is ordered irrespective of the actual demand.

Periodic review systems are applied in situations where the cost of operating continuous review systems is considerably high especially if the counting process for the items is difficult or expensive. However, with the improvements in information systems, continuous review systems has been made simpler and inexpensive thereby rendering continuous review systems as the most applicable inventory control systems in practice and have been argued to have greater cost saving potentials than periodic systems. This thesis only considers continuous review systems and as such further discussions or interactions between periodic systems and forecasting models will not be discussed for periodic review systems.

2.3.2 Continuous Review Systems

In their recent literature review on inventory management research, Williams & Tokar, (2008) showed that continuous review systems are the most widely used inventory control systems. Under these approach rather than periodically checking inventory levels as in the case of periodic systems, the continuous review systems recommends replenishments as soon as inventory positions falls below re-order point (s). From literature review several supply planning models can be used under this system.

The first one is the basic (s, Q) model introduced by Harris (1913) where a firm place orders of size Q, whenever its inventory position reaches a re-order point (s). In this case Q is the economic order quantity (EOQ). EOQ method optimizes the joint cost of ordering and holding inventory taking cognizance of the annual demand or demand planning horizon or expected demand during the lead time. It is made on the assumption that the rate of demand is constant. Because the EOQ model assumes a normal distribution, the re-order point (s) is obtained by using normal distribution and evaluated as the demand during lead time plus safety stock.

$$s = \mu_L + Z\sigma_L \qquad (10)$$

Where $Z\sigma_L$ = safty level;

μ_L = Mean demand during lead time = $\mu_{D*}L$

$\sigma_L = \sigma_D * (L)^{1/2}$

Z =Number of standard deviations for a specified probability

σ_L = Standard deviation of demand during lead time.

σ_D = Standard deviation of demand

L = Lead time in months

μ_D = mean demand

Under continuous review systems it is also possible to use the (S, s) system in which whenever demand reaches or goes below the re-order point (s) a replenishment quantity which is between the minimum and maximum level (S) is ordered. That is if inventory level (x) < re-order point (s), order (S-x) and if x>s do not order. There is also a possibility for (S-1, S) policy in which whenever there is any demand, the replenishment quantity is the quantity demanded. In other words, the maximum stock is S and an order is placed whenever the stock balance falls to S - 1. This policy is often supported for controlling the stock levels of expensive, slow-moving items (Schultz, 1990).

There are several methods for determining optimal order-up-to-level (S) for both (S, s) and (S-1, S) supply planning policy. One stream of research on the determination of optimal order-up-to-level (S) focuses on establishing the breakeven between quantities ordered and expected cost while considering the demand distributions. This methods is simular to the newboy problem where researchers have basically assumed that that the ordering process is characterized by fixed prices and uncertain demand and must decide how much quantity to stock taking cognizance of uncertain demand and knowing that piled up of excess and/or inventory in warehouse will be worthless over a period of time (e.g., perishable items). In this case, (S) is represented as:

$$S= \Phi^{-1} D \left(\frac{b}{\mathrm{b+h}}\right) \qquad (11)$$

h= is the holding cost per unit per period;

b= is the backorder cost per unit per period,

$\Phi^{-1} D$ = the inverse cumulative distribution function of the lead time demand (D).

Equation (11) is used depending on the distribution of demand that is assumed for the data. If the distribution of demand is assumed to be normal, then:

$$S= \mu + \sigma Z \left(\frac{b}{\mathrm{b+h}}\right) \qquad (12)$$

And the lead time demand will have mean($\mu_{DL)}$=$L\lambda\mu_x$ and standard deviation $\sigma_{DL} = \lambda L(\mu_x^2 + \sigma_x^2)^{½}$. If the distribution of demand is assumed to be lognormal (i.e., a random variable whose logarithm is normally distributed), then:

$$S = \mu e^{Z\,(b/b+h)\,\sigma} \qquad (13)$$

Teunter and Duncan (2009) used the service level to derive the order-up-to level (S) using lognormal distribution of lead time demand for intermittence demand items. By applying the inverse lead time distribution function (F), the order-up-to level is calculated as:

$$S = F^{-1}(SL) \qquad (14)$$

SL is the service level. If the distribution of demand is assumed to be unifrom distribution (i.e., known, finite number of equally inter-arrival demand is equally likely to happen), then:

S will be represented by Dmin + $(D_{max}-D_{min})*\left(\frac{b}{b+h}\right)$ (15)

Where D_{max} is the maximum historical demand and D_{min} is the minimum historical demand. If the distribution of demand is assumed to be poisson distribution, Babai et al. (2011) develop a simple method than can be used to calculate the optimal order-up-to-level in a single echelon, single item inventory system under a compound Poisson demand process and stochastic lead-times. In their model, unfilled demands are backordered. Consequently, optimal S is calculated as:

$$S = \left(\frac{b}{b+h}\right) - e^{-\lambda L} \qquad (16)$$

Where λ is mean demand arrival rate and L is the mean lead time. Poisson distribution is used to categorize demand arrivals in which the inter-arrival times are exponentially distributed and the individual demand size follows some unspecified discrete distribution. From the literature, Poisson assumption is usually utilized when the demand sizes between periods consist of large independent varying sizes.

The second stream of studies on optimal order-up-to-level derivation focuses on using the average monthly demands during months of demand. These method is better than the previous discussed methods for several reaosns. First, this method is relatively simple and easier to implement than the economic order quantity method and other methods discussed above. For example, there is no need to regularly compute ordering costs, such as labor and order processing as other method requires. Second, considering that demand patterns for intermittence demand items is usually unpredictable, a reorder order quantity which is based on stock-out probability has been argued to perform better than economic order quantity because economic order quantity assumes that the reorder order quantity will remain constant as demand remains constant. However, for intermittence demand items, demand often fluctuates and varies in sizes. Consequently, it invalidates the validity of the economic order quantity. A reorder order quantity based on stock-out probability is more appropriate than an economic order quantity and other methods discussed above.

The stock-out probability method is derived by adding average demand during periods with demand to the re-order point. One criticisms of this method is that it doesn't integrate holding or ordering costs into the reorder quantity. However, it has been argued that this method logically does the same effect as the EOQ, because the expected annual demand is uniformly distributed into equal batch sizes, which consist of monthly expected demand (Beacon et al., 2007).

If a possion process is choosen to derive reorder order quanity (S/Q), it makes sense that the same distribution is used to derived appropriate safety levels and re-order points (s). This is because the standard deviation for intemittence demand items is usually large entailing that demand fluctuates considerably high. Otherwise, if safety levels is derived under the assumption of normality(normal distribution), the derived safty levels will be estremely too large and posses a subtantial risks of carrying too much inventory since under this condition demand is assumed to be relatively constant. The poisson method enables the inventory planners to remove abnormalities or spikes in demand to derive re-order points and safety levels based upon average demand. Under poisson process, re-order points can be evaluated by taking into cognizance of the following:

L = Lead time in months

μ_D = mean demand

p = service level

OR by approximation, if the mean demand is greater than 30, the normal distribution is often been used to approximate the poisson distribution in calculating the re-order points and safety levels (Beacon et al., 2007). Thus:

$$(s) = \mu_{D*}L + Z^* (L + \mu_D)^{1/2} \qquad (17)$$

2.3.3 Lateral Transshipments and Multiple-Echelon Logistics Networks

Multi-echelon supply chains are complex supply chain networks with several echelons in which higher level echelons are usually used to serve lower levels echelons. Research in multi-echelon optimization has focused on providing the optimality of base stock policy for the multi-echelon, multi-item logistics network. One common strategy utilized for optimizing the multi-echelon logistics network is lateral transshipment. Lateral transshipment is the process of replenishing several networks or nodes from other networks within the same echelon logistics networks. This strategy enables organization to optimize the logistic network by minimizing total inventory cost, satisfying customer service levels and reducing stock-out risks.

Two main streams of literature on lateral transshipments can be identified. The first refers to proactive transshipment models where lateral transshipments are used to redistribute stock amongst all stocking points in an echelon at predetermined moments in time (Paterson et al., 2009). In this case, lateral transshipment decisions are organized in advance such that the handling costs are as low as possible. The second stream of literature refers to reactive transshipments which is delimited to take place at predetermined times before all demand is realized, or they can take place at any time to respond to stock-outs or potential stock-outs (Paterson et al., 2009).

Discussions on lateral transshipment are important when discussing forecasting especially for intermittence demand items. This is because both lateral transshipment models and improved forecasting aim to increase customer service levels while reducing backorder cost and inventory holding cost. On one hand most studies that focuses on demand forecasting only lay emphases on single echelon supply chain. On the other hand, most research in multi-echelon inventory systems assumes homogenous inventory policy for the entire inventory system even though the multi-echelon inventory comprises of different SKU’s with different demand patterns.

Studies explicitly linking the interaction between intermittence demand items to multi-echelon optimization are limited. Improved forecast accuracy is needed for multi-echelon optimization. In multi-echelon logistics network, it is important to separate intermittence demand from fast moving demand items and utilize different respective inventory control policies suitable for each demand type. This was particularly emphasized in the literature review that (s, Q) is not suitable for intermittence demand items and fast moving forecast estimates is not suitable for intermittence demand items. In their study on multi-echelon spare parts supply chain, Kalchschmidt et al. (2003) recommended separating demand patterns in their respective patterns and derive their respective ordering policies accordingly to enhance the operative performance of the inventory management of the case organization.

The focus of this thesis is not to derive optimization policy or base stock policy for one-echelon multi-item logistics network of the case company. This has already been researched by Heikkila (2011). Currently, there is monthly KPI's monitoring the performance of the single echelon optimization which has been recently implemented. To enhance the benefits of the Single-echelon optimization of the case company, this thesis will explore if the optimal forecasting model and corresponding ordering policies for intermittence demand estimates leads to any improvement in the already implemented single-echelon optimization.

2.4 Performance of Intermittence Forecasting Models

Several performance measures can be seen in intermittence forecast performance literature. The first stream of literature uses theoretically (traditional) generally measures such as MAD, RMSE, GRMSE, RE, PBt, MSE to evaluate performance of intermittence forecast models. The second stream of literature uses cost models such as backorder cost reduction, inventory holding cost reduction and total inventory cost reduction. A parallel stream of studies within the cost model also suggests a new cost method referred to as cost of forecast error. With this method, the forecast that proofs the least cost is seen as the best model.

The third stream of studies on forecast performance uses customer service levels to determine the performance of intermittence demand estimates. In this method, the forecast with the highest degree of customer service levels is selected as the best forecast performance method. Finally, some studies use composite measures by combining each of these streams. Consequently, the forecast model that optimally performs best across these combined methods is selected as the best forecast method for the intermittence demand estimate.

This section discusses these measures in more details and also discusses factors in empirical literature that has been shown to influence performance of intermittence demand estimates.

2.4.1 Traditional Methods

Several theoretically (traditional) generated methods have been used in empirical literature to select the best forecast model. The first set of methods is called scale dependent measures (Swanson et al., 2011). The most commonly used scale-dependent measures for forecast accuracy are based on the distributions of absolute errors (|E|) or squared errors (E^2), which is taken over the number of observations (n). These measures are:

Mean Square Error (MSE) = $\Sigma(E^2)/n$; (18)

Root Mean Square Error (RMSE) = sqrt(MSE); (19)

Mean Absolute Error (MAE) = $(\Sigma|E|)/n)$ (20)

Mean absolute error is most times called mean absolute deviation (MAD), even though MAD in its standard form differs from MAE. In this thesis they mean the same thing.

So far, both in practice and literature there is no outright criterion that have been established as a "good" value for any of the scale-dependent measures such as MSE; RMSE, MAE and MEDAPE (Swanson et al., 2011). How these measures are interpreted remains questionable. For example, as arithmetic means, the presence of outliers will influence MSE, RMSE, and MAE. Consequently, they will return greater weight to large error values because they weigh each of the errors or differences equally. One advantage of MAE is that it averages the errors ignoring their sign (Boylan et al., 2008) and it is moreover measured in the same units as the original data, similar in magnitude to, but slightly smaller than the RMSE (Swanson et al., 2011). The RMSE is advantageous over MSE because its scale is same as the forecast data. Consequently errors reported by the RMSE are description of the size of an "average" error rather than "average" of squared errors, as is the case for MSE (Swanson et al., 2011).

The second set of methods is called scale-independent measures. They use percentage error (PE) that is 100 $\left(\frac{e_t}{X_t}\right)$ or 100% $\left(\frac{X_t - X_{t-1}}{X_t}\right)$ ($X_t$is actual demand at time t and X_{t-1} is forecast at time t) to compare forecast performance across different data sets

Mean Square Percentage Error (MSPE) = $(\Sigma PE^2)/n$; (21)

Root Mean Square Percentage Error (RMSPE) = sqrt((ΣPE^2)/n); (22)

Mean Absolute Percentage Error (MAPE) = ($\Sigma|PE|$)/n; and (23)

$$\text{SMAPE} = 1/T \sum_{t=1}^{t} \left(\frac{|X_t - \ddot{x}_t|}{(X_t + \ddot{x}_t)/2} 100 \right) \quad (24)$$

Though, scale-independent methods show superiority over the scale dependent methods especially when the nature of forecast data has varying scale measures. However, when $\ddot{x}_t = 0$, the forecast error for scale-independent measures is infinite or undefined for any *t* in the period of interest. Thus, for intermittence demand with some periods of no demand, these measures will show undefined errors. One solution to that has been suggested by scholars is to include only those data that are positive. The application of this approach in practical forecasting systems is too complicated.

Furthermore, Symmetric Mean Absolute Error (SMAPE) has been shown to overcome this deficiency as it is possible to use it with zero demand. This is because of the symmetry of error characteristics of SMAPE that makes it possible to use it regardless of how large the demand is greater than the forecast or vice versa (Wallström & Segerstedt, 2010). Also, it was suggested by Makridakis & Hibon, (2000) that percentage error in SMAPE does not enlarged when the demand is close to zero. Both SMAPE and other scale independent measures do not have the ability to reveal systematic error (bias) (Wallström & Segerstedt, 2010).

The third set of theoretical measures is the method based on relative errors (r) represented as [$\frac{e}{e*}$]. This method divides each error by the error obtained using other forecasting model. One of the measures of forecast accuracy that is based on relative errors that have gained attention is the Geometric Root Mean Squared Error (GRMSE). Unlike MSE, RMSE and MAE that cannot annul the effect of outliers, GRMSE has the ability to handle lumpy demand. It was developed by Fildes (1992) and it is based on ratios. Consequently, it is both scale and unit-independent and can be used for groups of time series as well as controlling for the effect of outliers.

Geometric Root Mean Squared Error (GRMSE) of method M is:

$$GRMSE_m = \quad 1/N\left(\prod_{n=1}^{N}(F_{m,s} - A_s)^2\right)^{\frac{1}{2N}}$$

(25)

Where m is the forecasting method, *s* is the series being forecast, *F*m,s is the forecast from method m for series s and *A*s is the actual demand value for series s. Capital pi ∏ is the product of all values in range of series $\prod x_i = x_1 \cdot x_2 \cdot \ldots \cdot x$. $e^2 = (F_{m,s} - A_s)^2$. The relative GRMSE of method m compared to method n will be given as:

$$GRMSE_{M,N} = \prod[e^2_M / e^2_N]^{1/2n}$$

(26)

For interpretation purposes, a forecast method with GRMSE of 10% greater than the alternative forecast method has on average a 10% larger absolute error per series.

The scale independent measures have been criticized for their inability to deal with systematic error (bias) with exception from GRMSE which is not as severe as the other methods (Wallström & Segerstedt, 2010). Wallström and colleague introduce new theoretical accuracy measure-cumulative forecast error which has the ability to deal with systematic errors. Cumulative forecast error (CFE) is defined as the cumulative sum of all forecast errors. When using CFE measure, Wallström and colleague suggest that an unbiased forecast error during the period of forecast should be close to zero. For instance, cumulative forecast error is used as tracking signal to detect systematic changes in the demand and systematic error of the forecast method (Alstrom, & Madsen, 1996).

Tracking Signal = Cumulative Forecast Error/MAD (27)

MAD in this case is same as Mean Absolute Error (MAE). Tracking signal is independent of best-fit forecast type. Thus, it is not normally used to select a forecast type that performs best; rather it is used to track how well a certain forecast type is performing in meeting systematic changes in demand and forecast.

In software packages like servigistics, tracking signal of -4 to + 4 is used as within control-limits to detect this change. If the tracking signal tends towards plus means that forecast is less than demand and minus means that demand is less than forecast. If the tracking is zero implies that the number of times demand is greater than forecast is equivalent to the number of times forecast is greater than demand. The numbers (-4 to +4) is a rough estimates of number of times the difference between demand and forecast has occurred over the history period used for the forecast. However, this is greatly influenced by the presence of outliers. In other words, tacking signal does not track the magnitude of change in forecast error. This is because tracking signal is built on the premise that the distribution of demand is normal. If the distribution of demand is not normal, the number of signals outside of the control limits can be increased compared to a normal distribution (Wällstrom, 2009). To eliminate this problem, Makridakis & Wheelwright, (1989) suggested an analysis of the distribution of demand is needed to derive appropriate control limits. Distribution of demand for intermittence items is not normal as a result, tracking signal may not be appropriate for this type of demand patterns.

Additionally, if the denominator (MAD) is close to zero, tracking signal becomes bias. Though scholars have suggested the use of smoothing constants for the tracking signal to remove this bias, nevertheless, it still affects the possibility to detect changes (Makridakis & Wheelwright, 1989). As a result of the disadvantages of CFE, Wällstrom & Segerstedt (2010), proposed a new measure which combined CFE with other non-theoretical estimates i.e. stock control estimates. They proposed the use of period-in-stock (PIS) and number of shortages (NOS). This will be discussed more in the next section.

2.4.2 Stock Control Measures

As argued above, the traditional or theoretical generated forecast error measures are not appropriate for intermittent demand, even though they are regularly used in the literature. Recent scholars have called for cost-based or stock control measures that account for the stock-holding implications and customer service levels of several forecast models.

Eaves & Kingsman (2004) proposed the use of stockholding consequences of forecast estimates by deriving the order-up-to-level and their corresponding safety stocks, stock-on-hand after delivery. Based on this, they concluded that SBA led to a substantial cost savings in terms of reducing safety stock and stock on hand while meeting target service levels. Syntetos & Boylan (2006) utilized the non-parametric measure introduced by Sani and Kingsman (1997) that provides the relative measure of how much a forecast estimate performs better than the other estimate (APR). Average Percentage Regret (ARP) with respect to the average number of units of stock using forecast estimates x is represented as:

$$\text{StockAPR}_x = \frac{\sum_{i=1}^{n} \frac{S_{x,i} - \text{Min}_i}{\text{Min}_i}}{n}, \tag{28}$$

Where i is the particular demand data series under consideration; n is the total number of SKU's in the series, $S_{x,i}$ is the average number of units in stock as a result of the use of forecast estimator x on series i. Min_i is the lowest average number of units in stock achieved by one of the other forecast estimators considered on the same series i. They applied the APR measure on customer service levels (CSLAPRx) and argued that the SBA and SMA perform best with 90% to 95% customer service levels.

Boylan et al., (2004) proposed the use of customer service levels (ratio of fulfilled demand to total demand) and the average value and volume of stock holding to test for performance of forecast estimates. By deriving order quantity (cumulative forecast over lead-time) and the re-order point using appropriate distribution, they show that the SBA method led to 8.9% stock reduction than SMA estimate. This corresponds to 11.7% reduction of total inventory value and a slight reduction of customer service levels from 96.75% to 93.37%. Similarly, Syntetos et al. (2009) propose the use of customer service levels and total inventory holding cost and backlog cost for evaluating performance of intermittence demand estimates in a special case of periodic review system where lead time is shorter than the average inter-demand interval. They found out that the use of SBA led to cost reduction from 14 to 22% and the customer service levels remain unaffected with the introduction of the SBA method. The total savings was evaluated as the ratio of inventory holding charge per unit per period to the backorder charge per unit per period and their corresponding total cost. Ordering cost was not considered because no information was provided as it's often difficult to allocate these costs per SKU since purchase orders are usually placed collectively.

Furthermore, to focus more on tracking signals that reflect stock control measures, Wällstrom (2009) and Wällstrom & Segerstedt (2010) suggested the use of number of shortages (NOS) and period in stock (PIS). Number of shortages (NOS) during the investigated time interval is the number of times the cumulative forecast error is over zero (i.e. demand is greater than forecast). If cumulative forecast error is over zero means that there is positive CFE consequently there is a shortage. Thus, (NOS) reflects the number of shortages a forecasting method has without a safety stock. Wällstrom, 2009 suggest that NOS can be used as an indicator of bias such that when no value of NOS exists, it means that the forecasting method is creating a stock and where value of NOS exist, it means a few shortages or a lot of shortages exist and a bias problem exist. Its percentage is the quotient between NOS and number of demands and it is used to compare error between different items.

$$\text{NOSp} = \frac{NOS}{M} * 100 \qquad (29)$$

The problem with this measure (NOSp) as well as CFE is that it does not tell if a method or method current settings is increasing the stock or systematically underestimating the real demand. To correct these drawbacks, Wällstrom (2009) suggested the use of period in stock.

Period in stock (PIS) measures the total number of periods the forecasted items has spent in stock or number of stock-out periods (Wällstrom, 2009). A positive number indicates that the forecasting method tends to overestimate the demand and a negative number indicates the forecasting method underestimates the demand. The error measure is reversed and it is stated as demand subtracted from forecast.

Two other studies have emerged that tend to derive the cost of forecast error by appropriating cost to different inventory inputs that interacts with forecast estimates and suggest that the best forecast model are the models with the minimum cost of forecast error. Catt et al., (2008) in their study on assessing forecast model performance in an ERP environment develop a tutorial for calculating the cost of forecast error in a single item inventory system, where the cost of forecast error is calculated as the cost of safety stock holding and the cost of lost sales. From their model, the higher the safety stock level, the lower the lost sales and the lower the safety sock level, the higher the lost sales. Their model is represented as:

$$\text{Cost of Forecast Error CFE}^{1} = \left(\text{SSvr} + \frac{BM\sigma\sqrt{R \quad + LG(k)}}{R}\right)\text{P} \quad (30)$$

CFE^1 is the annual cost of forecast error in dollars; SS is the Safety stock in units; v is the unit cost in \$/unit; r is the inventory carrying charge, in \$/\$/month; B is the fractional charge of margin per unit short; M is the product margin in dollars; P is the period multiplier to convert from months to years; and G is the standard unit loss function (unit normal distribution).

Their optimal safety stock is derived from the service level ab-inito set by the case company. Their measure fall short of the followings: Catt & colleagues measure does not include the inventory control policy used. Inventory control policy determines how much to order and when to order. Different control policy gives different order quantities as a result should be considered in any stock control performance measure. More so, their service level derivation was based on fill rate as a result does not reflect customer's satisfaction of their services (customer service levels). Finally, their measure did not include cycle cost holding and ordering cost.

Nguyen et al. (2010) extended the Catt and colleagues measure to include inventory control policy and customer service levels. In their measure (s, Q) continuous review systems was used which included the customer service levels or fill rates (CSL). Three steps were identified for calculating the cost of forecast errors (CFE^1).

Step 1: Optimize the (s, Q, CSL^r) inventory control system with known demand which returns optimal values for s_d, $Q_{d,}$ realized fill rates CSL^r and total inventory cost $TC_d(s_d, Q_{d,} CSL^r)$.

Step 2: Optimize the (s, Q, CSL^t) inventory control system with forecast estimates which returns optimal values for s_f, $Q_{f,}$ target fill rates CSL^t and total inventory cost $TC_f(s_f, Q_f CSL^t)$..

Step 3: Cost of forecast error is then calculated as $CFE^1 = TC_f(s_f, Q_{f,} CSL^r) - TC_d(s_d, Q_{d,} CSL^t)$.

Total Cost (TC) is considered as the sum of ordering cost, holding cost and backordering cost. The advantage of Nguyen and colleagues method is that they are easy simple to understand and implement and contains composite dimensions of inventory control cost which other authors have used singular aspects in their measures. More so, Nguyen measures can be used to monitor monthly or quarterly forecast key performance indicators. Target cost of forecast error can be set quarterly and used as part of inventory control performance measures used in managerial decision making for inventory management.

One important summary that could be drawn from these measures is that each measure has its own advantage and disadvantage. Table 3.0-4.0 shows the models used for intermittence demand forecasting, how the outcomes were determined and the actual outcomes of their methods. It is also obvious from Table 3.0-4.0 that studies using the traditional error measures have not particularly in all instances shown ambiguous support for any intermittence forecast model. For example, Eaves & Kingsman (2004) explored the performance of Croston, SBA, SES and SMA using MAPE, MAD and RMSE and concluded that the results vary and no single forecasting model emerges as the overall best using the traditional measures.

Table 3: Forecast Accuracy Measures, Smoothing Constants for Intermittence Demand Estimates

Authors	Forecast Models	Performance Measures	Smoothing Constants α/β	Results
Wiilemain et al (1994)	Croston, SES	MAPE, MDAPE, MAD, MSE	0.01, 0.1, 0.05	Croston performs better
Eaves & Kingsman (2004)	Croston, SES, SBA, SMA	MAD, RMSE, MAPE, costs		SBA reduces stock holding
Syntetos & Boylan (2005)	Croston, SES SBA & SMA	RGRMSE,PB, PBt	0.05, 0.10, 0.15, 0.20	SBA performs better
Synetetos & Boylan (2006)	Croston, SES SBA, SMA	PBt, APR	0.05, 0.10, 0.15, 0.20	SBA & SMA performs better
Boylan & Syntetos (2007)	Croston, SES, LS	MSE	0.10, 0.20	Croston performs better
Boylan et al (2008)	SBA, SMA	GRMSE, MAE, CSL, Stock volume & value		SBA reduces stock volume, value & CSL
Teunter & Sani (2009)	Croston, LS, SBA, SY	Bias & Variance	0.10, 0.20, 0.30	SBA performs better than other models
Teunter & Duncan (2009)	Croston, SES, LY, SY, Bsrp	MAD, MSE, RGRMSE	0.10, 0.15, 0.20	Croston, SBA & Bsrp performs better
Wallström & Segerstedt (2010)	Croston, LY, SBA, SES	MAD, MSE, SMAPE, CFE, PIS, NOS	0.05, 0.10, 0.15, 0.20, 0.25/0.2	SES performs better

Table 4: Forecast Accuracy Measures for Intermittence Demand Estimates

Authors / Measures	MAD	MSE	MAPE	SMAPE	RGrmse	PBt	CFE	SH	CSL	SC	AB	PIS
Eaves & Kingsman (2004)												
Croston												
SES												
SBA			(+)					(+)				
SMA	(+)											
Syntetos & Boylan (2005)												
Croston												
SES												
SBA					(+)	(+)						
SMA												
Synetetos & Boylan (2006)												
Croston												
SES												
SBA									(+)	(+)		
SMA									(+)			

Authors / Measures	MAD	MSE	MAPE	SMAPE	RGrmse	PBt	CFE	SH	CSL	SC	AB	PIS
Boylan & Syntetos (2007)												
Croston		(+)										
SES												
LS												
Boylan et al (2008)												
Croston												
SES												
SBA								(+)	(+)			
SMA												
Teunter & Sani (2009)												
Croston												
SY											(+)	
SBA		(+)										
LS												
Syntetos et al (2009)												
SBA									(+)			
Teunter & Duncan (2009)												
Croston									(+)			
SBA									(+)			
SMA												
Bootstrapping (Bsrp)									(+)			
Wallström & Segerstedt (2010)												
Croston												
SES		(+)					(+)					(+)
SBA	(+)	(+)										
SMA												
LY				(+)								

PBt =Performance Best
CFE =Cumulative Forecast Error
SH=Stock-Holding cost
CSL=Customer Service Levels
SC=Shortage Cost
AB=Average Absolute Bias
PIS=Period in stock

Furthermore, from table 3-4 authors have used α and β constants ranging from values 0.01 to 0.3. Some authors combined traditional and stock control forecast accuracy measures (e.g., Eaves & Kingsman, 2004; Teunter & Sanni, 2009; Wallström & Segerstedt, 2010) while some other authors used only traditional measures (Boylan & Syntetos, 2007) and stock control measures (Teunter & Duncan, 2009; Boylan et al., 2008) respectively.

Finally, Wällstrom (2009) in his licentiate thesis on evaluation of forecasting techniques and forecast errors made recommendation regarding suitable errors for intermittent demand. His findings suggest that MSE is sufficient for intermittent forecast model. While MAD is not suitable because it distort under the presence of outliers and SMAPE distorts when both forecast and demand is zero which may be the case for intermittent demand items.

The different measures of forecast errors favor different forecast models and the best method differs from measure to measure. For instance, MAD and MSE favours forecast models that can forecast closest to zero when demand is low with a few demand occasions (Wallström & Segerstedt, 2010). As a result, scholars have suggested that the traditional models are not enough for estimating forecast models especially for intermittence demand items and have called for new methods that will take cognizance of stock control performance (Teunter & Duncan, 2009; Tiacci & Saetta, 2009). In addition, Wallström & Segerstedt (2010) show with principal component analysis (PCA) that if theoretical generated measures are to be used, they provide relevant information when combined with other stock-control performance measures. For example, they suggested that cumulative forecast error (CFE) in conjunction with period-in-stock (PIS) or the Quotient of number of shortages to number of demand (NOSp) can be used for forecast accuracy measure as they traced bias more reliable than if only CFE is used. The quotient of NOSp and PIS was recommended as stock control tracking signal to replace the traditional tracking signal (CFE/MAD).

It is pertinent to note that the choice of forecast method should not always be based on measurements of forecast errors but also on the consequences for the organization (Wällstrom, 2010). In the same vein as the argument goes with traditional measures of forecast accuracy, there is far reaching need for stock control tracking signal which makes managerial meaning for practitioners. The Quotient of NOSp to PIS is a positive step, but the implementation in the practitioner's perspective may be difficult. For instance considering the continuous or stochastic procurement of parts and sales, keeping track of the period in stock may be complex especially when consumption does not always take all stock quintiles in inventory. Additionally, in some cases, available stocks are subjected to quality checks and material movements. As a result, keeping track of the exact stock which has been left in stock would be complex. For this reason, I recommend the amended version of Wällstrom (2010) which is the Number of Positive Forecast errors per review Period (NOPe); Number of Negative Forecast error per review period (NONe) and the measure of the degree of outliers within the forecast review period (ώp)

Stock Control Tracking Signal = [NOPe; NONe; ώp] (31)

Where ώp is a measure of outlier given as:

ώp = [X-μ]>nσ

N can take a value of 1 to 5 and μ is the mean of the of demand data; σ is the standard deviation of the demand data; X is the current demand data. If we choose an outlier detection of +2, implying that when ώp is greater than twice the standard deviation, then a value of [+4; -4; 2] would imply that forecast has been greater than demand four times using the implemented forecast type and demand has been greater than forecast four times and the current error in forecast has deviated twice the standard deviation of the demand series. This can be combined with Demand value and Demand Volume criteria to prioritize items that demand more forecast review attention for the inventory planners. The advantage of this method is that it tells how many times error and how much deviation in demand has occurred. Thus, unlike the ab-initio tracking signal, it tells the magnitude of the deviation. The disadvantage of this method is that it does not update itself after review period. One way to control for this is to use the latest 12months for the calculation. The values of NOPe; NONp and ώp can be subject to organizational requirements.

2.4.3 The Effect of Smoothing Constants on Forecast Accuracy

Table 2.0 shows the values of smoothing constants that has been used in previous empirical studies on intermittence demand forecasting. The values of these smoothing constants are between the ranges of 0.05 to 0.3. Defining the optimal values of the smoothing constants with respect to the different forecast models remains inconclusive.

The use of low α values in the range of 0.05-0.20 has been recommended in the literature on intermittence demand estimates (Croston, 1972; Johnston and Boylan, 1996; Syntetos and Boylan, 2005, 2006; Gutierrez et al. 2008). In their study on lumpy demand forecasting, Gutierrez et al. (2008) used the four α values of 0.05, 0.10, 0.15, 0.20, and found out that SBA method performs better than Croston and SES with $\alpha = 0.05$ in a 24 months' time series data.

Using traditional forecast accuracy measures and a hold-out sample of 500 items equally composing of different demand patterns, Eaves (2002) showed that different smoothing constants will imply different stock-holding consequences for Croston, SBA and SES method. Teunter & Duncan (2009) performed a sensitivity analysis by varying the smoothing constant within the 0.1–0.2 range and found out that the smoothing constant does have some effect on the performance of methods, but this effect is small in comparison to the difference in performance between the various forecast models.

Thus far, empirical studies showing the optimal values for smoothing constants for different demand patterns and their corresponding forecast model is yet established. As a result, attempt will be made in the empirical section to find optimal values for which the forecast models perform best using different demand patterns.

2.5 Theoretical Framework

The objective of this thesis was to test which forecasting models performs better for intermittence demand items for KONE global spares supply unit. In doing so, the thesis also aim at finding the optimal inventory control policy for intermittent demand items and to explore if the optimal forecasting model and control policy enhances the performance of the multi-echelon optimization. When this objective has been achieved, the thesis also shows a summary on how these results were implemented in the case organization.

To provide answer to these objectives, literature review on relevant issues in forecasting, inventory, logistics and supply chain management was explored. In developing the theoretical framework, I took cognizance of relevant literatures that can be implemented within the current inventory management system. I also took cognizance of relevant framework that are easy for managerial understanding and decision making.

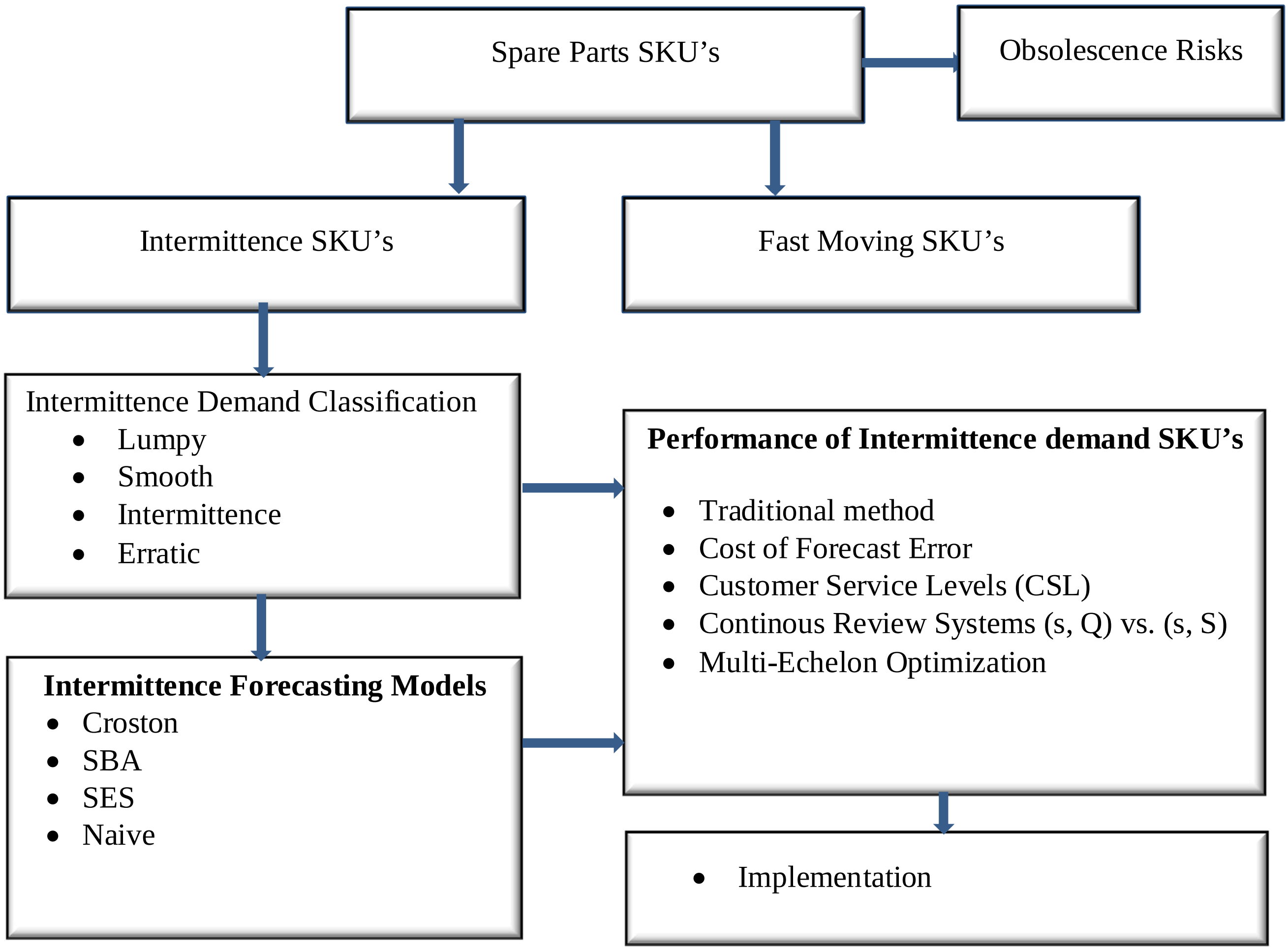
In section 2.0 and 2.1 the literature discussed several forecasting model for intermittent demand estimates and the need for forecasting based SKU classification that enables the selection of appropriate forecasting models. The forecasting models that will be explored are:

- Crotons model
- Simple exponential smoothing
- Naive model
- SBA model

This thesis will classify the SKU based on the forecasting based SKU classification and will validate which of these forecasting models performs better using this typology. The criterion for intermittence was SKU with mean inter-arrival period within the range 1.25 to 11 within the last twenty four periods. The reason is that if mean inter-arrival period is about greater than or equal to twelve periods, the inventory management system does not plan these items. These items are usually considered obsolescence risks items which current development in the case organization is to use advance demand information to manage this items or to change them to non-stock items which are basically delivered from supplier location to customers when there is sales order.

To provide answer to research question one, the impact of forecast models on customer service levels, traditional forecast accuracy measures and total cost of forecast will be tested. Stock control measures are combined with traditional measures because traditional accuracy measures tend to provide more meaning when combined with stock control measures (Wallström & Segerstedt, 2010). Although the case company software planning systems provide the possibility for accuracy measures based on MAE, MAPE and RMSE. This study will utilize MAE and MSE considering the arguments in the literature review regarding the strengths of MAE and MSE over MAPE for intermittence forecasting. For instance, as was discussed in the literature review, the presence of some periods of zero demand makes MAPE and other scale-independent measures inadequate for accuracy measure of intermittence items. Rather than using RMSE, MSE which is just the square of RMSE will be utilized. The reason for this is to enable comparison of the findings of this study with that of previous studies which have mainly shown that SBA performs better using MSE. Additionally, considering that MAD and MSE favors SES than Croston and SBA. SMAPE will further be employed to test for forecast performance.

Figure 5: Theoretical Framework:



To provide answer to research question two, the thesis will focus on continuous review systems and will test which of (s, Q) and (s S) performs better for intermittence demand estimates.

To provide answer to research question three, that is the link between forecast accuracy and multi-echelon optimization. I will follow up KPI's for the single-echelon optimization after the implementation of the best forecast accuracy measure to validate if improvement in intermittence demand forecasting in multi-echelon supply chain can significantly enhance multi-.echelon optimization. The new tracking signal suggested in these studies will not be explored. This is because it is beyond the scope of this thesis. It will be subjected for further research in the future. Finally, answer to research question four vis-à-vis implementation issues are discussed in section 4.3.4.

3. METHODOLOGY

3.1 Mixed Method in Single Case Study

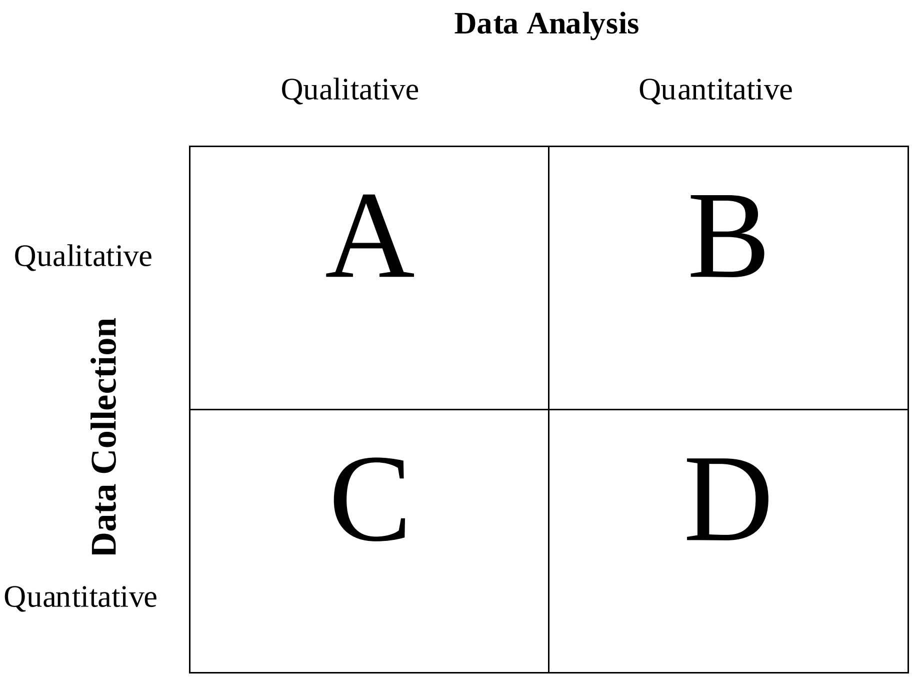
Mixed method is a type of research in which the researcher combines elements of qualitative and quantitative research approaches (e.g. the use of qualitative and quantitative viewpoints, data collection, analysis, inference technique) for the broad purposes of breadth and depth of understanding and corroboration" (Johnson et al., 2007).

Mixed method research is seen as one of the three major research paradigms: qualitative, quantitative and mixed methods (Johnson et al., 2007). A review of history of mixed method as a paradigmatic stance reveals that mixed method evolved from several periodic contributions. These contributions range from the debate on singular and universal truth to the call for multiple triangulations (Johnson et al., 2007). Several other contributions include: The call for multiple research methods, types of triangulation, advantages of combining quantitative and qualitative methods, and how to use methodological pluralism to improve the weakness stemming from a single paradigmatic approach (Johnson et al., 2007).

Mixed methods are used in supply chain and logistics research, but no comprehensive methodology has been researched on the potential of mixed methods in the supply chain and logistics discipline. Wynstra, (2010) recently reviewed 351 articles published in the (European) Journal of Purchasing and Supply Management, from the start in 1994 until the end of 2009 and concluded that there are ten major types of research strategy: 1) Literature review; 2) Meta-study; 3) Single case study; 4) Multiple case study; 5) Survey; 6) Expert interviews/ Focus group; 7) Field experiment; 8) Laboratory experiment; 9) Action research; and 10) Quantitative Modeling. He also find out that there are ten main data collection methods: 1) Primary quantitative data; 2) Secondary quantitative data; 3) Historical archive retrieval; 4) Participant observation; 5) Outsider observation; 6) Interviews; 7) Mail questionnaire; 8) Electronic questionnaire; 9) Telephone questionnaire; and 10) Face-to-face questionnaire.

Hurmerinta-Peltomäki & Nummela (2006) provides a yardstick to explore the application of mixed methods in the international business (IB) discipline. Their study classified mixed methods in the IB discipline based on the degree of application of quantitative and qualitative measures in the data collection and data analysis stage of the research design. Their study is based on the literature review of four top IB journals; Journal of International Business Studies, Journal of World Business, International Business Review and Management International Review.

Figure 6: Classification Tool for Mixed Method Studies



Their study suggests thirteen applications on how to mix in mixed methods research. Out of these thirteen proposed application only six models could be seen to have been explored in the IB discipline. B type is research designs in which the data collection is done qualitatively but analyzed quantitatively. C designs are research designs in which the data collection is done quantitatively but analyzed qualitatively. AB entails qualitative data collection with both qualitative and quantitative data analysis. AC entails qualitative and quantitative data collection with only qualitative data analysis. AD entails qualitative data analyzed qualitatively and quantitative data analyzed quantitatively etc.

Recently, there is call for the potential of mixed methods in case studies. Hurmerinta & Nummela (2011) analyzed how mixed methods can be used in case studies suggesting between method triangulation as against the dominant within method triangulation that has characterize the qualitative research designs. They suggested two types of strategy for the application of mixed methods in case study research. Compartmentalized strategy is the strategy in which the case is an independent part of the larger study and it is analyzed qualitatively and in the rest part of study, quantitative data collection and quantitative analysis is done. Thus, quantitative and qualitative data’s are analyzed within their own tradition (Hurmerinta & Nummela, 2011). Aggregated Strategy is the strategy in which the data collection is integrated and analyzed and interpreted jointly. According to them, quantitative data and analysis often dominates and different methods are intertwined and sequentially order is often difficult to identify.

The chosen mixed method strategy for this thesis is that of AD entailing that qualitative data is analyzed qualitatively and quantitative data analyzed quantitatively. The case is not an independent part of any larger study as Hurmerinta & Nummela, (2011) suggests in their compartmentalized strategy.

Furthermore, the methodology for this thesis is in the form of an experiment. An experiment is when a researcher changes the values of the independent variables in order to measure the size of the effect among dependent variables (Lundahl & Skärvad, 1999). As an experiment, the thesis made changes to the independent variables that have been tested in previous studies in order to measure the size of the effect among the dependent variables. The independent variables in previous studies have been forecasting models and the dependent variables have been forecasting error measures. In this thesis, I introduced additional independent variable which is the naïve model. I also introduced additional dependent variable such as control policy performance measure and cost of forecast error which has not been used for intermittent demand estimates.

3.2. Data Collection

The mixed method strategy was chosen based on the fundamental principle of mixed research (Johnson & Onwuegbuzie, 2004; Johnson & Turner, 2003). Thus, I ensured that the qualitative and quantitative methods and approaches are combined in a way that produces complementary strengths and non-overlapping weaknesses. In other words, the data collection method is done in such a way that will provide all of the information that is possibly relevant to the purpose(s) of the study.

Quantitative data analysis derived from primary data source will be used for testing the application of the forecasting models. The quantitative data comprise of historical demand information from 2010-2012 (36 Months period) for sixty eight thousand stock keeping units (SKU) in the three central distribution centers of the case company. Algorithms for the different forecasted models was developed and simulated against the demand data. Re-order points, economic order quantities (s, Q) and order up to levels (s, S) are derived. The simulation model is made in visual basic using excel as a platform. The model is a continuous review system and uses the forecast obtained from the simulation model to estimate the average demand during lead time and also make an estimate of the future variance so that the uncertainty of the forecast can be utilized when determining when to place an order.

Forecast for January-December 2012 is calculated based on 24months actual demand data from January 2010 to December 2011. Forecast performance is evaluated based on the difference between actual demand in 2012 and forecasted demand across several performance measures such as cost of forecast errors (CFE[1]), Geometrical root mean square error (GRMSE), Root mean square error (MSE) and Mean Absolute error (MAE). Customer service levels (CSL) is included in the Cost of forecast errors calculation.

The explorative/inductive part requires qualitative approach to data collection. Face-to-face qualitative interviews with the various stakeholders (Team members in Inventory planning team, Team leaders responsible for technical and purchasing) is done to explore the new spare parts introduction process and how the outcomes of the thesis can be implemented in the chosen organization. The improvement in the new spare introduction process will not be reported. However, as about 30% of the new spare parts constitute part of the intermittence demand parts, they will be treated under this overall forecasting thesis.

My role as an insider in the case organization, deeply involved in the subject under study makes it similar to ethnographic sense-making research approach. I was employed in summer 2012 as a summer trainer in the case company. By the end of the training my contract was extended as an inventory planner to work on the thesis research problem and implement the outcomes of the thesis. My daily tasks include inventory planning, forecasting, dead and excess stock management. This role gave me identity as an organizational member and created strong social ties between me, the organizational members and the subject under research. I had access to data, members and management necessary to facilitate the research and implementation process. This may however result in my sympathetic interpretations of the process. As put by sense-making researchers Vaara, (2003): “To which extent can the researcher go in pointing to the actions of a particular persons as causes of problems” This was however remedied by approaching the issue under research as a needed change opportunity for the organization and by seeking the opinions of all stakeholders on how to improve the current forecasting and dead stock problems in the company so that everyone feels a contributor in the change process rather than a cause.

3.3 Data Analysis

SKU’s was derived from the inventory planning software-Servigistic. SQL was used to upload thirty six months demand information from 2010-2012. A total of sixty eight thousand SKU’s was found. The breakdown of the SKU’s per distribution center is shown below:

Table 5: Number of SKU’s in three Distribution Centers

Distribution Centers	No. SKU's
A Distribution Centre	50,654
B Distribution center	8124
C Distribution center	9248

Twenty-four months historical demand data (Jan, 2010-Dec 2011) is used to forecast demand for Jan, 2012 to Dec, 2012. For the forecast data (Jan, 2010-Dec 2011), Visual Basic was used to develop codes to check for intermittence i.e. calculate the average demand interval or average inter-arrival time. When intermittence items were selected based on average inter-arrival time of 1.25 in the last 24 months, the number of intermittence SKU’s is shown in Table 6.

Table 6: Distribution of SKU’s Demand Pattern’s

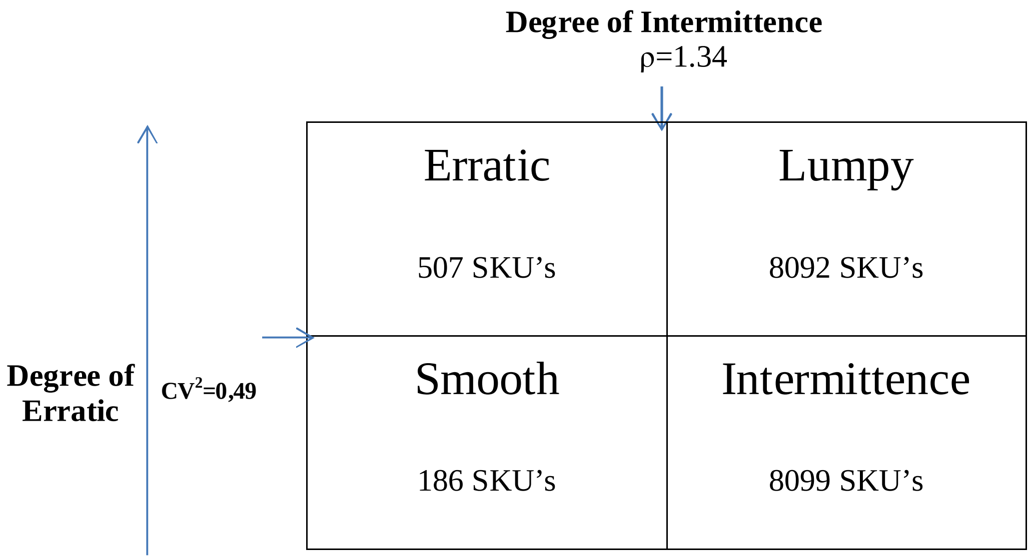
Fast Moving ρ <1.25 7,736	SKU's with zero demand in 24 months (Dead stock) 26,809
Intermittence ρ >=1.25<12, =16884 SKU’s	Obsolescence Risks SKU’s ρ >=12 = 2,505SKU’s
SKU’s with Less than 1 year history =15,000SKU’s	

The reason for eliminating items with ρ >=12 from the sample is because of two reasons. First, items with twelve or more than twelve months of no sales are considered as obsolescence risk items and the software do not plan most of these items. Secondly, most of these items are usually changed to non-stock items when the inventory stocks changes to zero. Non-stock means that these items are purchased directly from the suppliers and sold to the customers without stocking in distribution centers.

One interesting thing we saw from the data is that when intermittence is selected based on average inter-arrival time of 1.25 in the last 12 months, the distribution of number of intermittence SKU differs. But the differences are insignificant considering that our sample is a broader representation of all types of intermittence demand patterns. More so, almost 15000SKU's were excluded from the sample because they had less than 1 year sales history. The software used for inventory planning chooses Croston based on items with at least one year historical demand data.

From the sixteen thousand, eight hundred and eighty four intermittent demand items, the distribution of intermittence according to demand size and average time interval factors is shown in Figure 7.

Figure 7: 24-Months Period Distribution of Intermittence Demand Size and Average Inter-Arrival



The first demand interval and demand size was chosen to be the start value for the forecast. Some authors have suggested the use of the mean for the whole forecast period be the start value. However, in this thesis, the first demand interval and demand size is chosen.

3.4 Reliability and Validity

To ensure validity I ensured that the measures for forecast accuracy do not peculiarly fit a particular forecast model. To do that I used both traditional and stock control measures. To ensure reliability, I ensured that I repeated test of forecast performance using all the error measures. One way of ensuring reliability is by triangulation. According to Yin, (1994), there are four types of Triangulation: Data triangulation, Investigator triangulation, Theory triangulation and Methodological triangulation. Similar to Wällstrom (2009), I ensured triangulation by counting the number of first places each forecast model performs best than other models using the different performance measures.

4. FINDINGS OF THE STUDY

This section discusses the findings of the study. The first section discusses inventory classification and control policy in KONE. Next, forecasting models and accuracy measures in GSS KONE will be discussed. Finally, results from the data analysis are discussed and recommendations are made regarding the best forecast performance model and accuracy measure for intermittent demand items. Summary and conclusions are discussed and recommendation for future studies is stated.

4.1 Inventory Classification & Control Policy in KONE

Inventory classification in the case organization is based on demand-value classification (ABC) and Demand volume classification (XYZ). These classifications are used to derive optimized fill rates and safety levels meant for optimization of the single-echelon logistic network. The XYZ classification is also used to determine which items are taken to stock from those items that are stocked in supplier locations. In this case, 20% of highest moving X-items with minimum of six sales hits within the latest twelve months are changed from supplier stock location to own stock location.

Criticality analysis is used in the case company when evaluating stocking decisions in somewhat narrow dimension. Criticality from the case company perspective are items that when they get faulty may lead to the malfunction or non-operation of the equipment. The application of criticality in a more robust sense to include other issues relating to supplier risks and back-order cost is still very much needed in the case company.

The software system has possibility for selecting intermittence based on 1.25 inter-arrival periods. Consequently, has the possibility to separate fast moving items from slow moving items. This makes the system not only able to make selection of SKU's based on demand-value and demand-volume, but also classify inventory based on appropriate levels necessary to select adequate forecasting models. However, the system has the original Croston method for forecasting intermittent demand which several studies has so far shown to have positive bias. As proposed by Schultz (1990), the Croston has two smoothing constants for the inter-arrival time and demand size.

Servigistics has two order planning systems, time-phase planning and Trigger phase planning. The time phase planning uses forecasted values to derive Economic Order Quantities, Re-order point and other inventory optimization parameters. Time phase planning enables the placing of orders while looking forward in time, whereas, Trigger phase planning uses historical demand to derive Economic Order Quantities, Re-order point and other inventory optimization parameters. The disadvantage of time phase planning is that forecasting far in the future reduces forecast performance as a result, chances are that there will be increasingly excess inventories. The disadvantage of trigger phase planning is that it will compromise service performance.

The next section discussed the accuracy methods utilized followed by the result of the data analysis which will discuss which of naïve, SBA, Croston, SES, performs better for intermittent demand estimates using traditional measures and stock control measures.

4.2 Forecasting Accuracy Measures in GSS KONE

The accuracy model used in the case company is a combination of tracking signal and MAD, RMSE and MAPE. The tracking signal of -4 to +4 is used as control limit by the case company to detect systematic changes in the demand and systematic error of the forecast method. Similar to the literature review, the tracking signal measures the quotient of cumulative forecast error to mean absolute deviate over the forecast period. As we noted in the literature review, the problem with this measure is that it is not suitable for intermittent demand items considering that the denominator is MAD. In cases when demand and forecast may be zero, the tracking signal may tend to infinity suggesting errors as a result would not be suitable to detect systematic changes in the demand and forecast method. The distribution of demand for all SKU's is not normal. For the fast moving items, the distribution of demand is normal. Whereas, for the slow moving items, the distribution of demand is that of Poisson distribution and negative binomial distribution. Consequently, the use of tracking signal for intermittent demand items may lead to increasing number of signals outside the control limits.

The choice of forecast method used by the case company is chosen based on the method that results in the smallest forecast error over the specified history. This is done by calculating the average of MAD, RMSE and MAPE for all time periods in the specified history period. As we saw from the literature review, the traditional measures are not suitable for measuring intermittent demand items (Exception to MSE which Wällstrom, (2009) recommends that it is sufficient for intermittent forecast estimates. In the following section, we will see the outcomes of the traditional methods and stock control measures.

4.3 Performance of Intermittence Forecasting Models

Table 7 shows the number of intermittent SKU's in the three distribution center. Table 8 also shows the descriptive statistics of the inter-arrival time and coefficient of squared variation (CV^2).

Table 7: Sample of Intermittence SKU's in the Three Distribution Centers

Distribution Centers	No. SKU's
A Distribution Centre	14095
B Distribution center	1145
C Distribution center	1644

Table 8: Descriptive Statistics of Mean Inter-arrival Time and Coefficient of Squared Variation

Descriptive Statistics	Mean Inter-Arrival	CV^2
Standard Deviation	2,057847335	0,775418
Mean	3,413165316	0,707027
Minimum	1,25	0
Maximum	11	12,15771

The mean of the average inter-arrival time and the squared coefficient of variation is 3.4 and 0.7 respectively. It means that on average the SKU's have about 3-4 months of zero demand within forecast review period and the periods of zero demand deviate about twice from the average inter-arrival times having 11 months and 1.25 months of zero demand as the maximum and minimum period of zero demand. The mean value of coefficient of variation is 0.7 but they deviate about 0.8 from the mean value of the coefficient of variation. This implies that on average we have a good representation of datasets representing both erratic and non-erratic demand patterns (see Figure 7).

4.3.1 Traditional Methods and Accuracy of Demand Estimates

Table 9 shows the accuracy of intermittence demand estimates using traditional methods. Similar to existing studies, the performance of these methods varies from the accuracy measures used.

Table 9: Accuracy of Intermittence Demand Estimates β=0.2 (All points in time)

Values	MSE (Decreasing Order of Performance)	MAE (Decreasing Order of Performance)	Type
0,05	SES; SBA,CR; Naive	SBA; SES; CR; Naive	Lumpy
0,1	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Lumpy
0,15	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Lumpy
0,2	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Lumpy
0,3	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Lumpy
0,05	SES; SBA,CR; Naive	SBA; SES; CR; Naive	Erratic
0,1	SES; SBA,CR; Naive	SBA; SES; CR; Naive	Erratic
0,15	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Erratic
0,2	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Erratic
0,3	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Erratic
0,05	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Smooth
0,1	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Smooth
0,15	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Smooth
0,2	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Smooth
0,3	SBA;SES; CR; Naive	SBA; SES; CR; Naive	Smooth
0,05	SES; SBA,CR; Naive	SES; SBA,CR; Naive	Intermit
0,1	SES; SBA,CR; Naive	SES; SBA,CR; Naive	Intermit
0,15	SBA;SES; CR; Naive	SES; SBA,CR; Naive	Intermit
0,2	SBA;SES; CR; Naive	SES; SBA,CR; Naive	Intermit
0,3	SBA;SES; CR; Naive	SES; SBA,CR; Naive	Intermit

For lumpy items, SBA performs better for α value in the range of 0.1-0.3 using MSE, while SES performs better using α value of 0.05. For Erratic items, SBA performs better for α value within the range of 0.2-0.3. While for values within the range of 0.05-0.1, SES performed better. For Intermittent category, SES performed better for all α values from 0.05-0.1 while SBA performed better from 0.15-0.3.

Using MAE, SES performed better for all α values within 0.05-0.3 for intermittent items. While for Erratic and Lumpy items, SBA performed better for all α values from 0.05-0.3, while for Smooth items, SBA performed better for all α values from 0.05-0.3.

In addition, I did check if a change in β values from 0.2 to 0.3 would led to a consistent performance of SBA for lumpy and erratic items for α values at 0.05. The result yielded no significant changes. Furthermore we tested the performance of the forecast at periods immediately after demand, there no significant changes noted but a consistent performance of

SBA over other forecast methods. Interestingly, the findings are similar to the findings of Wallström & Segerstedt (2010) where SBA and SES exert superior performance over Croston.

These findings also suggest that there is significant need to separate intermittent demand into their constituent's types. When intermittent types are not classified based on their different types, the findings suggest that SES exert superior performance in general using traditional performance measure.

When SMAPE was used as forecast accuracy, Croston performs better than SBA, SES and Naive. As SES has a greater ability to forecast closest to zero reinforces its somewhat superior performance over Croston and SBA using MSE and MAD. However, when SMAPE is utilized, it became obvious that Croston performs better than SES. Due to the extreme poor performance of Naive method using the traditional method, it was excluded from further analysis under this thesis.

4.3.2 Stock Control Methods and Accuracy of Demand Estimates

Customer Service Levels was derived from the fraction of demand than could be satisfied. By deriving economic order quantities and re-order points (Equation 17), I calculated the fraction of demand that was able to be satisfied using the different forecasting models. From the analysis, there is 1% customer service level difference between Croston and Simple Exponential Smoothing. Thus, implementation of Croston increases customer service levels by 1%. There is about 1.4% customer service level between Croston and SBA. Thus, Croston led to an increase of customer service level by 1.4%. This findings reinforces the over estimation bias of Croston which would definitely increases total stock value. To limit the over-estimation of Croston, α value should not exceed 0.15. At this level, the over-estimation or bias is reduced.

When performance was explored on the basis of total stock quantity, SES will lead to the minimal total stock quantity followed by SBA and Croston. The difference in reduction of total stock quantity varies depending on the value of α used. When α is less than 0.15, Croston had the best CSL and a negligible difference in total stock quantity over SBA. However, Croston had about 5% increases in stock quantity compared to SES.

Though not included in the research question, I explored the relationship between forecasting and obsolescence rate. This is because of the obsolescence challenges facing the organization. I considered a special case of sudden death of obsolescence of 2200 spare parts that had no consumption for the following 12months. It is possible some of these parts were not actually dead but where harmonized or replaced with other fast-moving similar parts. In other to calculate the total cost incurred by the organization if an intermittent item becomes suddenly death, I calculated the total cost incurred due to the last economic order quantity recommended under the assumptions of these different forecasting models. The total annual cost incurred as a result of procured economic order quantity before the sudden death of obsolescence is given as:

$$TC = OC\left[\frac{EOQ}{2}\right] + HC * P[\frac{D}{EOQ}] \qquad 32$$

Where OC =ordering cost

HC= holding cost

EOQ= Economic Order Quantity

D = Annual forecast

P = Unit price of item

It was found out that, if we assume α at 0.05 levels and β at 0.2, Simple Exponential Smoothing would lead to the lowest obsolete cost while Croston and SBA would lead to about 2% increase in total cost incurred respectively as a result of obsoleteness. SBA has about 1% reduction in total cost over Croston as a result of obsoleteness.

To explore the total cost incurred by forecast models, I excluded the case of sudden death of obsolescence from the sample and calculated the effect of each forecasting model on total cost using the same formula above (32). It was observed that a change in the forecasting model from SES to Croston will lead to 1% increase in total cost. While a change from SES to SBA will lead to 0.29% increase in total cost. A change from SBA to Croston will lead to 0.22% increase in total cost. It should be noted that the total cost derivation above does not include the backorder cost. Including backorder cost extends our understanding of total cost not limited to cost of ordering and holding cost, but also includes cost of lost sales. The organization does not have an estimate for back-order cost, but the increase in customer service levels for the implementation of Croston would entail a lesser back-order cost compared to simple exponential smoothing and SBA methods. Other models of forecast error would have been considered, but the absence of backorder cost significantly influence the consideration for the total cost model in equation 32.

Furthermore, I explored the relationship between forecast estimates and inventory control policy. The influence of forecasting on inventory control models yielded significant effect depending on how the order up-level is derived. For this thesis, I use the simplistic model (average values of non-zero demand in the forecasted 12 months). The result showed a reduction in total cost and stock value while compromising customer service levels (6% reduction in customer service levels).

Finally, at the time of the closure of the thesis, the implementation of the multi-echelon optimization was just concluded. Consequently, I'm unable to report the substantial improvement in multi-echelon optimization. However, improvement in customer service levels by 1% if Croston is implemented could substantially impact the performance of the multi-echelon optimization.

4.3.3 Research Questions and Findings

The aim of the first research question was to: ***Test which of these forecasting models: crotons models, simple exponential smoothing model, naive model and (same as last year forecast) perform better for intermittence demand items for KONE global spares supply unit.***

This was explored by means of, traditional accuracy measures (MSE, SMAPE and MAE), customer service levels and cost of forecast error. Using traditional methods, no single estimate performed best across all accuracy measures. This is similar to the findings of Eaves & Kingsman (2004), that the results vary and no single forecasting model emerges as the overall best using the traditional measures (MAPE, MAD and RMSE) for Croston, SBA, SES and SMA. However, some insights can be drawn. Croston shows superior performance using SMAPE. SBA shows superior performance for MSE and MAE in a good number of times than Croston and SES. Although, empirical studies have shown that MSE favors SES, but the superior performance of SBA over SES using MSE leaves us with conclusion that SBA performs better. Additionally, considering the performance of Croston using SMAPE allows me to argue that while SBA performs s better, Croston is next to it using traditional accuracy measures.

Table 10: Stock Control Performance of Intermittence Demand Estimates

Performance Measures	Croston	SES	Croston	SBA
CSL	+1%		1.4%	
Stock Quantity	+5%		negligible	
Obsolescence rate (TC)	+2%		+1%	
TC	+1%		+0,22%	

Regarding, stock control measures, Table 10 shows outcomes of forecasting methods across customer service levels and total costs. As stated previously, there is 1% customer service level difference between Croston and Simple Exponential Smoothing. There is about 1.4% customer service level between Croston and SBA. These findings leads to the conclusions that Croston leads to increase in customer service levels compared to SBA and SES. Regarding total cost, Croston lead to 1% increase in total cost. While a change from SES to SBA will lead to 0.29% increase in total cost. A change from SBA to Croston lead to 0.22% increase in total cost. Though, the total cost derivation does not include the backorder cost, but the empirical findings leads me to conclude that Croston will increase the total cost. Based on the aforementioned, SBA will be the best forecast model for the case company.

The aim of the second research question was to: ***test which inventory control policy (s, Q) vs. (s, S) in continuous review systems maximizes the advantages of the best forecasting models for intermittence items.***

Using the simplistic model, (average values of non-zero demand in the forecasted 12 months), the result showed a reduction in total cost and stock value while compromising customer service levels

(6% reduction in customer service levels). Considering the importance of customer service level for the organization, the (s, Q) policy performs better for the case company.

The aim of the third research question was to: ascertain if ***improvement in intermittence demand forecasting improve multi-echelon optimization.*** I was unable to provide answer for this at this moment because the outcomes of the thesis is still under implementation and it will take at least a quarter or more before these can be proven.

The aim of the fourth research question was to: ***Explore how the results of the thesis can be implemented in the case organization.*** The implementation process and issues are discussed in section 4.3.4 below

4.3.4 Implementation

In other to implement the findings of the study, I explored the current state of forecasting parameters in the system and discussed with the management regarding the findings and possible implementation.

On exploring the forecasting parameters which is currently in place, there was need to review outlier management and tracking signal. Outlier management significantly influences the forecast estimates. The outlier management comprises of outlier detection, outlier correction and the maximum number of outlier occurrence allowed. The outlier detection is given a value n between 1 and 5 such that outliers are detected when the difference between actual demand and average historical demand is greater than n standard deviation i.e.

Outlier Detection = $(X-\mu)>n\sigma$

Then, outlier correction is the value subtracted from the actual outlier demand estimates. The default value for the system is between n values ranging from 1 to 5. The values subtracted from the outlier is given as the difference after subtracting the sum of the mean historical demand and n standard deviation from the actual outlier estimate. That is:

Outlier Correction = $X-(\mu + n\sigma)$

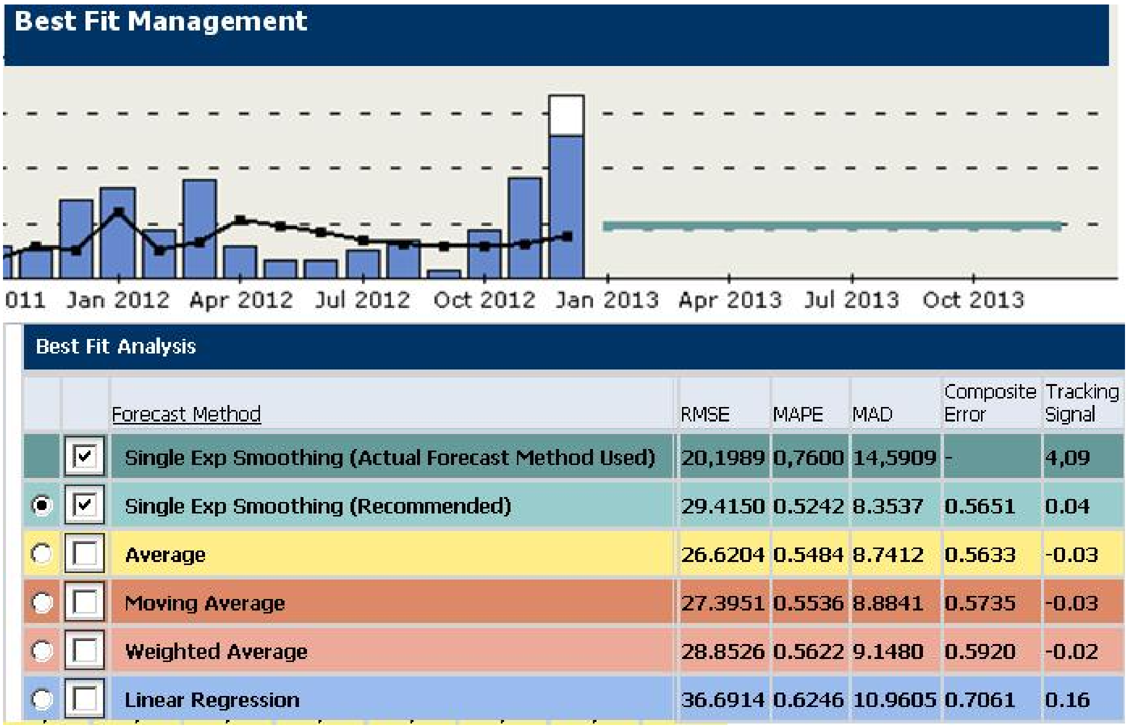
Finally, the maximum number of outlier allowed depicts how many times the outlier correction will occur hence it returns the outlier estimates as normal demand estimates. This value ranges between 0 and 5.

The current settings for outlier detection, correction and maximum allowed are 3 respectively. Under this condition, I carried out trial test based on actual demand history deriving forecast estimates and economic order quantities. The result of this test showed that the quantity of demand (outlier correction) subtracted under this settings is too low. Consequently its effect on EOQ and forecast estimates was still high. I recommended n value of 2 [i.e. Outlier is detected IF ABS[X-μ] >=2σ. A value of 2 for outlier correction 2 [i.e. Outlier correction = X- (μ +2σ)].

Figure 8: Servigistic Review Board Page Showing Review Reason 138

As discussed in the earlier findings, a tracking signal of [+4; -4] is currently used in the system to detect how well the best-fit forecast method is performing relative to demand. The system recommends review types 139 when tracking signal is less than -4 and 138 when tracking signal is greater than +4. Thus tracking signal of -4 shows that forecast is greater than demand roughly four times and +4 shows that forecast is greater than demand roughly four times. The number of this review types is alarming. Currently, the number of this review reasons is about 11,288 and a one inventory planner can only review about 200-300 within one working day. The current tracking signal is located in the best-fit performance segment which is not visible on the review board and currently does not have any filter. Figure 8 shows the current view of the review board when 138 review reasons is selected and Figure 9 shows the location of tracking signal on Best Fit page in Servigistics.

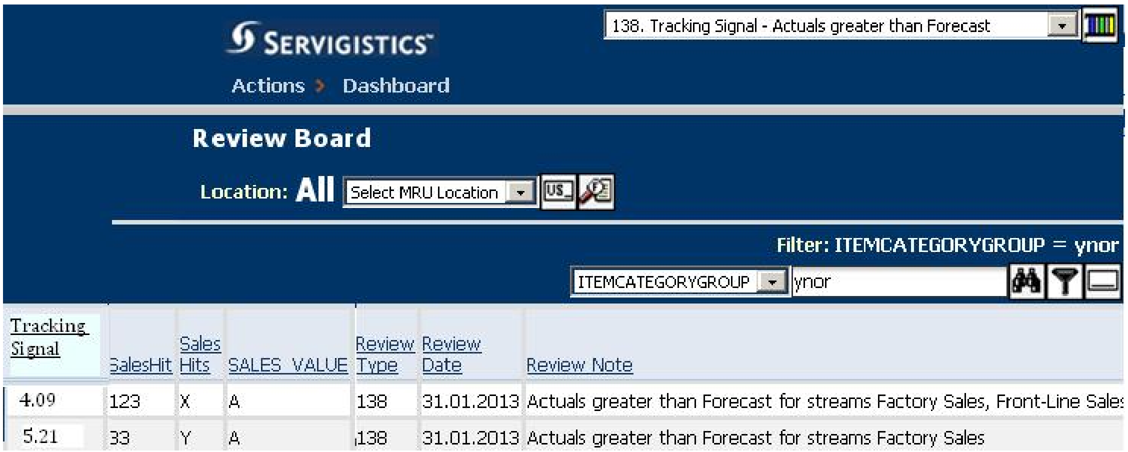
Figure 9: Servigistic BestFit Page Showing Tracking Signal



Forecast Method	RMSE	MAPE	MAD	Composite Error	Tracking Signal
Single Exp Smoothing (Actual Forecast Method Used)	20,1989	0,7600	14,5909	-	4,09
Single Exp Smoothing (Recommended)	29.4150	0.5242	8.3537	0.5651	0.04
Average	26.6204	0.5484	8.7412	0.5633	-0.03
Moving Average	27.3951	0.5536	8.8841	0.5735	-0.03
Weighted Average	28.8526	0.5622	9.1480	0.5920	-0.02
Linear Regression	36.6914	0.6246	10.9605	0.7061	0.16

On exploring the reasons for this review types, it was found out that the use of SES for intermittent items is also contributing significantly to these review types as SES does not update itself when there is no demand. The implementation of intermittent demand estimates such as Croston or SBA will reduce the number of these review types. Furthermore, at no occasion will forecast estimates be exact as demand consequently there will always be numerous amount of these review types. A test was carried out on the tracking signal and how it influences the forecast review types. The outcomes shows that even when there is forecast review reason 138 and 139 which was not reviewed by inventory planners during the month of the review reason. A 45-47% percentage change in forecast error in the succeeding month can automatically eliminate the review reason without any action from the inventory planners. Consequently, I recommended that a filter should be created so that tracking signal can be used for the review reasons 138 and 139. This will allow inventory planners to filter those review reasons with the greatest number of tracking signal estimates [far lesser than -4 and far greater than +4]. Example of how this can be implemented is show in Figure 10. This can further be filtered based on part value and frequency of orders.

Figure 10: Creating Filters for Tracking Signal Estimates



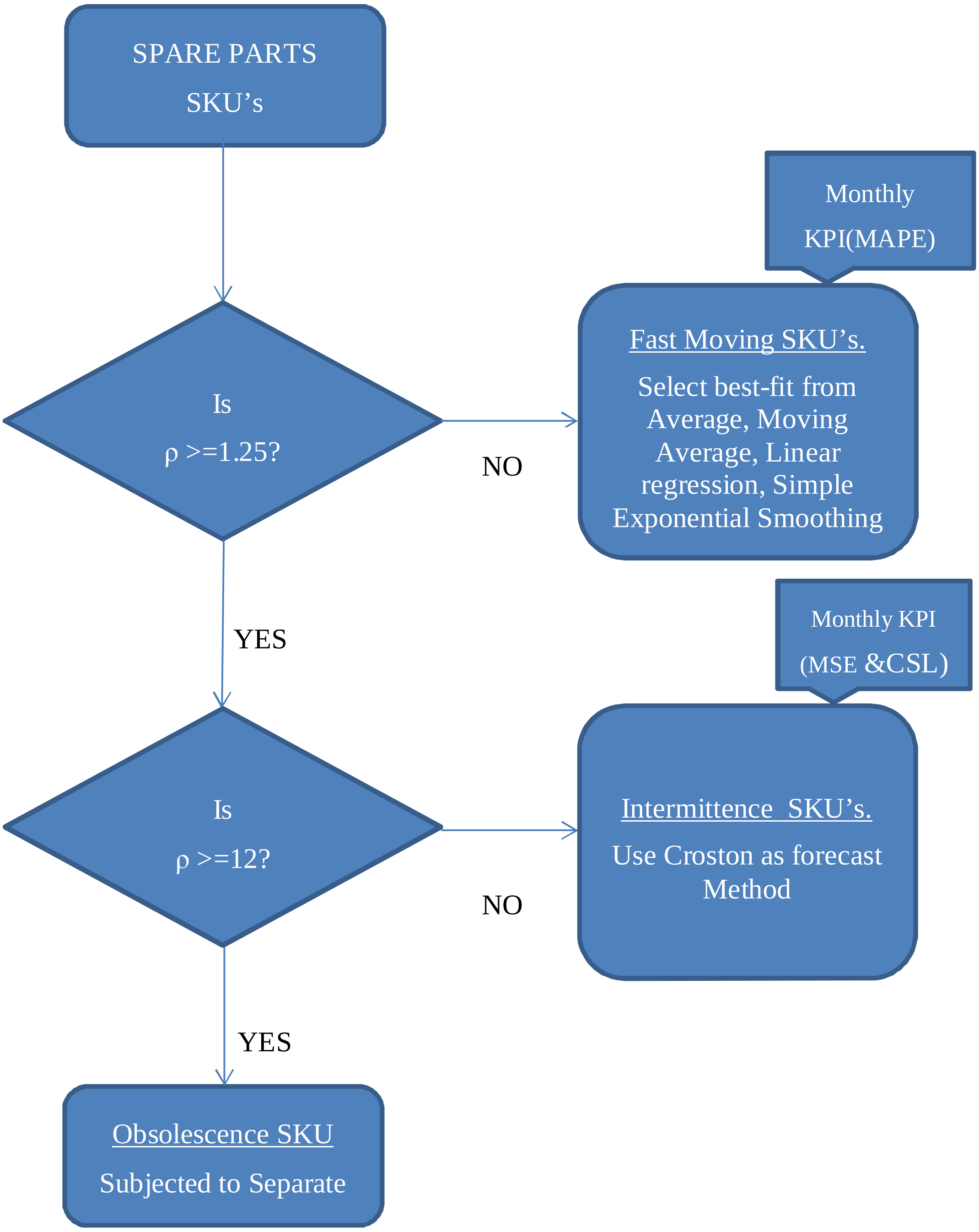
In addition, to the above recommended actions for implementation, the following recommendation was made regarding forecast estimates for intermittent demand items. Under the current system, I recommend the implementation of Croston for intermittent demand estimates rather than the current method which is a combination of SES, Average method, weight moving average and linear regression selected on the best outcome from MAPE. Furthermore α value should be kept between 0.05 and 0.2 and β values should be kept at 0.2. In the long run, if it is possible to customize the system I recommend that SBA be used for Erratic and Lumpy demand types while MSE can be used as best-fit to select between Croston & SES for smooth items and intermittent items at ρ >1.34.

Table 11: Recommendation of Forecast Estimates for Implementation

Options	Forecast Type	Types of Intermittent Pattern	Remarks
1	Croston	All Intermittent Items	Should be used under the current system
2	SBA	Erratic & Lumpy Items	Recommended for customization
	CR	Smooth intermittence	Recommend for best fit with SES
	SES	Smooth intermittent Items	Recommend for best fit with Croston

After discussion with the inventory planning team and the manager of the team, the first option was recommended for implementation alongside the other recommendations for outlier management and tracking signal.

Figure 11: Implementation of Croston



The implementation of Croston is shown in Figure 11. From the figure, when intermittence is greater than 1.25 but less than 12 within 24months historical period, Croston is selected. More so, 12months.is required as the minimum historical period required for intermittence to be estimated and the possibility for Croston to be selected. However, when intermittence is less than 1.25, the items are considered as fast moving spare parts. Consequently are subjected to best-fit estimate using MAPE. SKU's with intermittence greater than 12 are subjected to obsolescence stock management process. This is a separate process developed to manage items subject to excesses or obsolescence.

Furthermore, monthly, KPI's were developed to monitor how the forecast is performing in terms of customer service levels for both fast-moving and intermittence demand spares. However, MAPE and MSE were used respectively as traditional accuracy measures to augment the stock control measure. At the time of completion of this thesis, when MAPE was estimated for fast moving spares it was at 74% accuracy (i.e. 16% forecast error). MSE for intermittence items were still under-development. SQl code is required for this to be implemented in the current system i.e. servigistics.

5. CONCLUSIONS

Forecasting is an important topic that demands substantial managerial resources in spare parts business. Organizations are adopting several software packages to improve their inventory management and optimization. However, before the implementation of standard inventory software packages it is recommended that organizations should study the nature of their business, demand pattern and recommend customizable solutions that is applicable to the nature of their business.

The first aim of this thesis was to test which of the forecasting models Crotons models, Simple Exponential Smoothing model, Naive model (same as last year forecast) perform better for intermittence demand items for KONE global spares supply unit. The findings suggest that when traditional method (MSE, SMAPE, MAE and MAPE) of forecast accuracy is used, the performance varies significantly depending on which traditional measure is used. This is because, it has been suggested that some traditional measures favors some forecasting model than others. When MSE is used, SES performs better than Croston, SBA and Naive. When SMAPE was used Croston performs better than SES, SBA and Naive. More so, the performance varies significantly depending on the type of intermittent demand pattern. When intermittence is classified based on degree of erracticness and degree of intermittence SBA performs significantly better at increasing α value from 0.1 to 0.3 especially for lumpy and erractic items. While for intermittent categories, SES performs considerably better using MEA for all alpha values. However using MSE, SES performs better at alpha values less than 0.1. This reinforces the need for categorization of intermittent demand into its constituent's types before selection of appropriate forecast types.

Using stock control measures, the thesis aim to test which inventory control policy (s, Q) vs. (s, S) in continuous review systems maximizes the advantages of the best forecasting models for intermittence items. The (s Q) policy performs better with regards to customer service levels. However total cost is higher for (s, Q) control systems than (s; S) systems. The customer service levels reduction for (s, S) systems is around 6 percent reduction. However, the derivation of optimal S used may be the result of this reduction in service levels. Future studies can use other models and test its performance compared to (s, S). I found out that even though Croston did not perform absolutely best than SES and SBA using the traditional methods of forecast accuracy, it performed better using customer service levels. This validates the arguments of previous findings that the traditional measure of forecast accuracy should not be used alone to determine forecast performance.

The implementation of Croston using the sample size of about sixteen thousand SKU's lead to about 1% increase in customer service levels against SES and 1% increase in total cost. However, as against SBA, Croston would lead to about 1.4% increase in customer service levels. This findings is similar to Boylan et al. (2008) in their case study on forecasting and stock control in a continuous re-order point (s), order quantity (s, Q) control system who found about a reduction in customer service level from 96.75% to 93.37% when SBA was implemented. As with the positive bias of Croston, we saw an improvement of service levels by 1% than SBA which has been also been criticized for been negatively biased.

Due to the improvement with customer service levels with the implementation of Croston, this thesis validates the findings of other studies (e.g., Boylan et al. 2008; Syntetos et. al, 2009), that the implementation of Croston leads to reduction in backordering cost. Interestingly, sudden death of obsolescence which is a challenge with spare parts could be a draw back for Croston. Recently, authors (e.g., Teunter et al. 2011) have started to link intermittence forecasting models that control for obsolescence rate by providing no forecast values after several periods of no demand. The improvement in software and programming makes it easy to restrict order recommendation for items with no demand for certain period of months. The improvement of forecast accuracy alone cannot guarantee dead stock management. There is need for the case company to invest resources on future studies on proactive dead stock management combining both stochastic approaches and supply chain management approaches.

Outlier management and tracking signal correction was recommended for the case organization to improve the accuracy of forecast estimates. More so, Croston was recommended for implementation. However, in the long run, SBA could be used for lumpy and erratic items while Croston and SES could be subject to Best Fit management.

Other limitation of this study is that I was unable to utilize other ways for derivation of optimal order-up-to levels which would have thrown more light on the relationships between forecasting and stock control policy. Future studies can attempt this. More so, future studies can attempt to test the cost of forecast error measures as stock control measures for intermittence demand estimates. Finally, future studies should attempt to link forecasting to multi-echelon optimization and such research-ship should focus on deriving forecast models optimum for different demand patterns within the echelon network.

Managerial Contribution

First, monthly or quarterly forecasting KPI's which utilizes both traditional accuracy measures and stock control performance measures for management is a good managerial tool to have a holistic understanding of forecast performance. However, when doing this, care must be taken to ensure that demand patterns are separated in terms of fast moving and intermittence demand and appropriate measures of accuracy are applied.

Second, forecasting algorithms are not the fit-it-all solutions to forecasting challenges in spare parts business. Tracking signals are needed to keep track of how forecast estimates are performing over time. Additionally, advance demand information is also a means to improve forecast accuracy. Spare parts managers should aim at developing relationships with key accounts and use advance demand information to improve forecast accuracy especially for intermittent valuable spare parts.

Third, SBA is highly recommended for forecasting lumpy and erratic items. Croston and Simple Exponential Smoothing method can be selected based on best-fit of MSE for forecasting smooth intermittence and intermittent demand patterns. However, items at risks of obsolescence (items with no sales for twelve or more months) should be excluded from these items and a separate management effort is needed for this type of items.

Fourth, the empirical data reveals a greater percentage of dead and excess inventory were new spare parts. Some new spare parts usually have intermittent patterns before they become fast moving. There is need for management to develop robust tools for stocking decisions to reduce the rate of new spare parts that end up as excess or dead inventory.

Finally, before implementing inventory planning software packages, management should carry out this type of studies aimed at understanding the relationship between there demand patterns, control policy and performance. This will enable them to customize solutions that are peculiar to their organization in the software at the time of implementation. This is because as most inventory planning software's are standardized solutions, the failure to make this customization at the initial stage of adoption, may however lead to commitment of more resources and change management efforts.

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APPENDICES